# Essays on asset pricing: comparisons of factor models, investigations of the roles of illiquidity, R&D investment, product market competition, and labor mobility

by

**Ziwen Bu**

A thesis submitted for the degree of
Doctor of Philosophy in Finance and Risk

**Nottingham University Business School**
**University of Nottingham**

December 2018

Copyright © 2018, Ziwen Bu

# Contents

**Contents** i

**List of Tables** ii

**List of Figures** iii

**Abstract** vi

**Overview** 1

**1 Best of the best: A comparison of factor models** 8

1.1 Introduction . . . 8

1.2 Factor models and anomaly portfolios . . . 12

1.2.1 Competing models . . . 12

1.2.2 Anomaly portfolios . . . 16

1.2.3 Model performance measures . . . 17

1.2.4 Tests for comparing cross-sectional $R^2$s . . . 19

1.2.4.1 Pairwise tests of equality of cross-sectional $R^2$s . . . 19

1.2.4.2 Multiple model comparison . . . 20

1.3 Time-series results . . . 20

1.3.1 Size-STR (short-term reversal) portfolios . . . 21

1.3.2 Size-CI (abnormal capital investment) portfolios . . . 22

1.3.3 Size-DR (distress risk) portfolios . . . 23

1.3.4 Size-$\beta$ (market beta) portfolios . . . 23

1.3.5 Size-NI (net share issues) portfolios . . . 24

1.3.6 Size-MAX (lottery demand) portfolios . . . 25
1.3.7 Size-RVar (residual variance) portfolios . . . 26
1.3.8 Size-AC (accruals) portfolios . . . 26
1.3.9 IND (industry) portfolios . . . 27
1.3.10 D10−1 (high minus low decile) portfolios . . . 28
1.3.11 Overall model performance in time-series regressions . . . 28
1.4 Cross-sectional results . . . 30
1.4.1 Size-STR (short-term reversal) portfolios . . . 30
1.4.2 Size-CI (abnormal capital investment) portfolios . . . 32
1.4.3 Size-DR (distress risk) portfolios . . . 32
1.4.4 Size-$\beta$ (market beta) portfolios . . . 33
1.4.5 Size-NI (net share issues) portfolios . . . 33
1.4.6 Size-MAX (lottery demand) portfolios . . . 34
1.4.7 Size-RVar (residual variance) portfolios . . . 35
1.4.8 Size-AC (accruals) portfolios . . . 36
1.4.9 IND (industry) portfolios . . . 36
1.4.10 D10−1 (high minus low decile) portfolios . . . 36
1.4.11 Overall model performance in cross-sectional regressions . . . 37
1.5 Conclusion . . . 38
Tables . . . 40
Appendix . . . 60

**2 Illiquidity, R&D investment, and the cross-section of stock returns 94**

2.1 Introduction . . . 94
2.2 The Model . . . 97
2.2.1.1 Technology of R&D . . . 98
2.2.1.2 Uncertainty . . . 98
2.2.1.3 Information and illiquidity . . . 99
2.2.2 Optimization . . . 101
2.3 Data, R&D intensity and illiquidity measures, and summary statistics . . . 101

2.3.1 Data and measures of R&D intensity and illiquidity . . . 102
2.3.2 Summary statistics . . . 104
2.4 Empirical results . . . 106
2.4.1 Cross-sectional regressions . . . 106
2.4.2 Cross-sectional regressions with illiquidity dummies . . . 109
2.4.3 Double-sorted portfolios . . . 111
2.5 Tests of alternative mechanisms . . . 113
2.5.1 Financial constraints . . . 113
2.5.2 Innovation ability . . . 115
2.5.3 Product market competition . . . 117
2.6 Conclusion . . . 119
Tables . . . 120
Appendix . . . 128

**3 Product market competition, labor mobility, and asset prices in the cross-section 156**

3.1 Introduction . . . 156
3.2 Hypothesis development . . . 158
3.3 Data and summary statistics . . . 159
3.3.1 Data and measures of product market competition and labor mobility 159
3.3.2 Summary statistics . . . 162
3.4 Empirical results . . . 164
3.4.1 Double-sorted portfolio analysis . . . 164
3.4.2 Cross-sectional regressions . . . 166
3.4.3 Cross-sectional regressions with market competition dummies . . . 167
3.4.4 Evidence from an extended sample . . . 169
3.5 Conclusion . . . 170
Tables . . . 170
Figures . . . 176
Appendix . . . 177

**Concluding Remarks** **188**

**Bibliography** **190**

# List of Tables


1.1 Performance of factor models in time-series (absolute) tests . . . . . 40

1.2 Overall performance of factor models in time-series (absolute) tests . . . . . 43

1.3 Tests of equality of cross-sectional $R^2$s: 25 size-STR portfolios . . . . . 44

1.4 Tests of equality of cross-sectional$R^2$s: 25 size-CI portfolios . . . . . 45

1.5 Tests of equality of cross-sectional $R^2$s: 25 size-DR portfolios . . . . . 46

1.6 Tests of equality of cross-sectional $R^2$s: 25 size-$\beta$ portfolios . . . . . 47

1.7 Tests of equality of cross-sectional $R^2$s: 35 size-NI portfolios . . . . . 48

1.8 Tests of equality of cross-sectional $R^2$s: 25 size-MAX portfolios . . . . . 49

1.9 Tests of equality of cross-sectional $R^2$s: 25 size-RVar portfolios . . . . . 50

1.10 Tests of equality of cross-sectional $R^2$s: 25 size-AC portfolios . . . . . 51

1.11 Tests of equality of cross-sectional $R^2$s: 30 IND portfolios . . . . . 52

1.12 Tests of equality of cross-sectional $R^2$s: 8 D10−1 portfolios . . . . . 53

1.13 Summary of factor model performance: Tests of equality of cross-sectional $R^2$s . . . . . 54

1.14 Multiple model comparison tests . . . . . 55

1.15 Summary of factor model performance: Multiple model comparison tests . . 59

1.A1 Factor correlations . . . . . 63

1.A2 Average excess returns and alphas of the 25 size-STR portfolios . . . . . 64

1.A3 Average excess returns and alphas of the 25 size-CI portfolios . . . . . 66

1.A4 Average excess returns and alphas of the 25 size-DR portfolios . . . . . 68

1.A5 Average excess returns and alphas of the 25 size-$\beta$ portfolios . . . . . 70

1.A6 Average excess returns and alphas of the 35 size-NI portfolios . . . . . 72

1.A7 Average excess returns and alphas of the 25 size-MAX portfolios . . . . . 74
1.A8 Average excess returns and alphas of the 25 size-RVar portfolios . . . . . 76
1.A9 Average excess returns and alphas of the 25 size-AC portfolios . . . . . 78
1.A10 Average excess returns and alphas of the 30 IND portfolios . . . . . 80
1.A11 Average excess returns and alphas of the 8 D10−1 portfolios . . . . . 82
1.A12 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-STR portfolios 83
1.A13 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-CI portfolios . . 84
1.A14 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-DR portfolios . 85
1.A15 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-$\beta$ portfolios . . 86
1.A16 (Sequential) Tests of equality of cross-sectional $R^2$s: 35 size-NI portfolios . . 87
1.A17 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-MAX portfolios 88
1.A18 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-RVar portfolios 89
1.A19 (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-AC portfolios . 90
1.A20 (Sequential) Tests of equality of cross-sectional $R^2$s: 30 IND portfolios . . . 91
1.A21 (Sequential) Tests of equality of cross-sectional $R^2$s: 8 D10−1 portfolios . . 92
1.A22 Summary of factor model performance: (Sequential) Tests of equality of cross-sectional $R^2$s . . . . . 93

2.1 Summary statistics: Full sample . . . . . 121
2.2 Cross-sectional regressions . . . . . 122
2.3 Cross-sectional regressions with illiquidity dummies . . . . . 123
2.4 Double sorts on illiquidity and R&D intensity . . . . . 124
2.5 Double sorts on illiquidity and R&D intensity after controlling for financial constraints . . . . . 125
2.6 Double sorts on illiquidity and R&D intensity after controlling for innovation ability . . . . . 126
2.7 Double sorts on illiquidity and R&D intensity after controlling for product market competition . . . . . 127
2.A1 Summary statistics: Preliminary sample . . . . . 131
2.A2 Summary statistics: All-but-microcaps sample . . . . . 132

2.A3 Cross-sectional regressions with industry dummies . . . 133
2.A4 Cross-sectional regressions: Extended sample period . . . 134
2.A5 Cross-sectional regressions: Returns adjusted for delistings . . . 135
2.A6 Cross-sectional regressions: 1975–2000 . . . 136
2.A7 Cross-sectional regressions: 2002–2016 . . . 137
2.A8 Cross-sectional regressions: High-tech and low-tech firms . . . 138
2.A9 Cross-sectional regressions: Illiquidity computed using 12-month data . . . 139
2.A10 Cross-sectional regressions with dummy variables: Illiquidity computed using 12-month data . . . 140
2.A11 Double sorts on illiquidity and R&D intensity: Illiquidity computed using 12-month data . . . 141
2.A12 Cross-sectional regressions: Illiquidity computed using 12-month data and updated yearly . . . 142
2.A13 Cross-sectional regressions with dummy variables: Illiquidity computed using 12-month data and updated yearly . . . 143
2.A14 Double sorts on illiquidity and R&D intensity: Illiquidity computed using 12-month data and updated yearly . . . 144
2.A15 Cross-sectional regressions: $RDAT$ as a measure of R&D intensity . . . 145
2.A16 Cross-sectional regressions with dummy variables: $RDAT$ as a measure of R&D intensity . . . 146
2.A17 Double sorts on illiquidity and R&D intensity: $RDAT$ as a measure of R&D intensity . . . 147
2.A18 Cross-sectional regressions: Amihud illiquidity . . . 148
2.A19 Cross-sectional regressions with dummy variables: Amihud illiquidity . . . 149
2.A20 Double sorts on Amihud illiquidity and R&D intensity . . . 150
2.A21 Double sorts on illiquidity and R&D intensity: $4\times4$ sort . . . 151
2.A22 Double sorts on illiquidity and R&D intensity: $5\times5$ sort . . . 152
2.A23 Double sorts on illiquidity and R&D intensity after controlling for financial constraints (Hadlock and Pierce, 2010) . . . 153

2.A24 Cross-sectional regressions after controlling for volatility . . . . . 154
2.A25 Double sorts on illiquidity and R&D intensity after controlling for volatility 155

3.1 Summary statistics . . . . . 171
3.2 Double sorts on product market competition and labor mobility . . . . . 172
3.3 Cross-sectional regressions . . . . . 173
3.4 Cross-sectional regressions with product market competition dummies . . . 174
3.5 Double sorts on product market competition and labor mobility: 1973–2016 175
3.A1 Summary statistics: All-but-microcaps sample . . . . . 177
3.A2 Double sorts on product market competition and labor mobility: 4×4 sort . 178
3.A3 Double sorts on product market competition and labor mobility: 5×5 sort . 179
3.A4 Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility . . . . . 180
3.A5 Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility: 4×4 sort . . . . . 181
3.A6 Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility: 5×5 sort . . . . . 182
3.A7 Double sorts on product market competition ($HAT$) and labor mobility: 5×5 sort . . . . . 183
3.A8 Double sorts on product market competition (Hoberg and Phillips, 2010) and labor mobility: 5×5 sort . . . . . 184
3.A9 Cross-sectional regressions: Product market competition (Hou and Robinson, 2006) . . . . . 185
3.A10 Cross-sectional regressions with dummy variables: Product market competition (Hou and Robinson, 2006) . . . . . 186
3.A11 Cross-sectional regressions: 1973–2016 . . . . . 187

# List of Figures

3.1 Returns on high-minus-low labor mobility portfolios . . . . . 176

# Acknowledgments

I would like to express my deepest gratitude to my thesis advisors, Sanjay Banerji and Shamim Ahmed, for their excellent scholarly guidance, profound patience, and constant supervision during the whole period of my PhD studies. But most importantly, I would like to express my infinite gratitude to my parents, Xiuxiu Wang and Tongjun Bu, for their unconditional love and encouragement throughout.

# Declaration

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that one paper titled "Best of the best: A comparison of factor models" drawn from Chapter One of this thesis has been accepted by the *Journal of Financial and Quantitative Analysis*, which is co-authored with Shamim Ahmed and Daniel Tsvetanov. The paper titled "Illiquidity, R&D investment, and the cross-section of stock returns?" drawn from Chapter Two of this thesis is co-authored with Shamim Ahmed and Sanjay Banerji, and is under review with the *Management Science*, while the paper titled "Product market competition, labor mobility, and the cross-section of stock returns" drawn from Chapter Three of this thesis is co-authored with Shamim Ahmed and Sanjay Banerji.

Ziwen Bu

December 2018

# Abstract

This thesis comprises three essays in asset pricing, with a focus on scrutinizing factor models and dissecting anomalies. In the first chapter, I compare major factor models and find that the Stambaugh and Yuan (2016) four-factor model is the overall winner in the time-series domain. The Hou, Xue, and Zhang (2015) $q$-factor model takes second place and the Fama and French (2015) five-factor model and the Barillas and Shanken (2018) six-factor model jointly take third place. But the pairwise cross-sectional $R^2$ and the multiple model comparison tests show that the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor and four-factor models, and the Barillas and Shanken (2018) six-factor model take equal first place in the horse race.

The second chapter proposes a model of research and development (R&D) venture, which predicts that the positive relation between the firm's R&D investment and the expected stock returns strengthens with illiquidity. Consistent with the model's prediction, empirical evidence based on cross-sectional regressions and double-sorted portfolios suggests a stronger and positive R&D-return relation among illiquid stocks. A further analysis shows that the important role of illiquidity in the R&D-return relation cannot be explained by factors such as financial constraints, innovation ability, and product market competition. Collectively, the results suggest that stock illiquidity is an independent driver of the R&D premium.

The third chapter investigates whether product market competition explains a significant portion of labor mobility premium. I hypothesize that the positive relation between labor mobility and stock returns is stronger (weaker) among stocks in competitive (concentrated) industries. Consistent with the hypothesis, the results indicate that labor mobility is a significant determinant of stock returns only in the cross-section of stocks in competitive industries, after controlling for size, book-to-market, short-term reversals, and momentum. Overall, these findings suggest that product market competition potentially and independently drives the positive relation between labor mobility and stock returns.

# Overview

This thesis comprises three essays in asset pricing, with a focus on scrutinizing factor models and dissecting anomalies. In the first chapter, I go beyond the vast majority of empirical studies by statistically comparing the performance of a much larger array of both classic and new-generation asset pricing models in explaining several prominent return anomalies. My array comprises the capital asset pricing model of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor model, the Asness and Frazzini (2013) three-factor model, the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the "high minus low" value factor, the Stambaugh and Yuan (2016) four-factor model, and the Barillas and Shanken (2018) six-factor model. Although recent research (see Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016) documents hundreds of potential traded and nontraded factors that explain the cross-section of stock returns, I limit myself to these traded factor models for two reasons. First, these models have survived as the prominent if not the best models over the years. Importantly, most of my chosen models are frequently used for risk-adjustment purposes in the empirical asset pricing literature (see, for example, Bali, Cakici, and Whitelaw, 2011; Bali, Engle, and Murray, 2016; Gu, 2016; Hirshleifer, Hsu, and Li, 2017; Kuehn, Simutin, and Wang, 2017). Second, focusing only on return factor models allows us to explore their performance in both the time-series and the cross-sectional domains. Moreover, given the plethora of models, investigating the ten prominent factor models keeps the model comparison exercise at a reliably manageable level. Hence, my empirical examination of the relative model performance can be viewed as a search for the best of the best factor pricing models.

As in many recent papers (see, among others, Fama and French, 2015, 2016, 2017; Hou, Karolyi, and Kho, 2011; Hou, Xue, and Zhang, 2015, 2017a; Stambaugh and Yuan, 2016), I begin by applying my chosen factor models to the data and informally comparing them using

a comprehensive set of pricing performance metrics estimated in the time-series domain. I then employ the pairwise test for equality of cross-sectional regression $R^2$s introduced by Kan, Robotti, and Shanken (2013). A key advantage of the sample cross-sectional $R^2$ test is that the testing procedure takes into account the impact of potential model misspecification and therefore ensures robust and valid statistical inference regarding relative performance. This also enables us to see how different are my informal findings on relative model performance in the time-series domain from those of the cross-sectional statistical evidence. However, the pairwise model comparison may not always determine unambiguously the best factor model when multiple models are involved in the horse race (Barillas, Kan, Robotti, and Shanken, 2017; Gospodinov, Kan, and Robotti, 2013; Kan, Robotti, and Shanken, 2013). To address this concern, I also conduct a multiple model comparison, following Kan, Robotti, and Shanken (2013), which identifies whether a "benchmark" asset pricing model significantly outperforms a set of alternative models in terms of the cross-sectional regression $R^2$.

To investigate the strengths and weaknesses of competing factor pricing models, choosing among test assets based on numerous predictive signals (see, for example, Green, Hand, and Zhang, 2014) is a challenge. In this regard, I follow prior empirical studies (see, among others, Fama and French, 1997, 2008, 2016; Feng, Giglio, and Xiu, 2017; Kan, Robotti, and Shanken, 2013; Kozak, Nagel, and Santosh, 2017; Stambaugh and Yuan, 2016), especially the suggestion of Lewellen, Nagel, and Shanken (2010), while keeping my analyses parsimonious. I choose subsets of test assets representative of major anomaly categories, such as investment, profitability, intangibles, and trading frictions, documented in the literature (see Green, Hand, and Zhang, 2014; Hou, Xue, and Zhang, 2015, 2017a,b, and references therein). Specifically, the sets of test assets used in this chapter are the value-weighted monthly excess returns on: the 25 size-STR (short-term reversal) portfolios, the 25 size-CI (abnormal capital investment) portfolios, the 25 size-DR (distress risk) portfolios, the 25 size-$\beta$ (market beta) portfolios, the 35 size-NI (net share issues) portfolios, the 25 size-MAX (lottery demand) portfolios, the 25 size-RVar (residual variance) portfolios, the 25 size-AC (accruals) portfolios, the 30 IND (industry) portfolios, and the 8 D10$-$1 (high minus low decile) portfolios. These test asset portfolios capture a vast cross-section of return anomalies; at the same time, a majority of them are readily available in the public domain, as described in the next section. More importantly, many of my test asset portfolios pose a greater challenge to existing asset pricing models (see, for example, Fama and French, 2016). Different from Hou, Xue, and Zhang (2017a) and Stambaugh and Yuan (2016), my rationale for using the eight sets of independent two-way sorted portfolios is that they allow us to see how well the competing

factor models accommodate anomaly returns across size groups. In fact, asset pricing models have systematic problems explaining average returns on small stocks (see Fama and French, 1993, 1996, 2015, 2016, 2017).

My time-series analyses using point estimates of an exhaustive set of pricing performance measures demonstrate that the Stambaugh and Yuan (2016) four-factor model is the overall winner among all the asset pricing models in explaining anomalies. For example, the model outperforms, though informally, the competing models by producing the smallest point estimates for the average absolute alpha and a variant of the alpha dispersion metric in half of the sets of test asset portfolios. Considering the metric measuring the dispersion (second moment) of the alphas due to sampling error, I see that the Stambaugh and Yuan (2016) four-factor model delivers the largest point estimate in four out of the ten sets of test portfolios. Moreover, the model generates the least number of statistically significant alphas for six portfolio sets. The Hou, Xue, and Zhang (2015) $q$-factor model does a reasonably good job in accommodating anomaly returns and takes second place in the horse race. For example, the $q$-factor model produces insignificant alphas for all 25 of the size-DR portfolios. The model also offers the largest point estimate for the dispersion (second moment) of the alphas, due to sampling error, in three sets of test asset portfolios. Among the remaining competing models, the Fama and French (2015) five-factor model and the Barillas and Shanken (2018) six-factor model perform about equally well and take equal third place. Both of them deliver the largest point estimate for the average time-series regression $R^2$ in five out of the ten sets of portfolios. Looking at the 42 small size portfolios across the eight anomaly variables, I find that all of my asset pricing models have difficulties explaining their returns – an observation consistent with prior studies.

When the model comparison exercises are carried out based on pairwise tests of equality of sample cross-sectional $R^2$s and multiple model comparison tests, a different but statistically valid picture emerges. Overall, I find that the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, and the Barillas and Shanken (2018) six-factor model, all perform about equally well, and so jointly take first place in the horse race. More importantly, these asset pricing models are never statistically dominated at the 5% level in any of my multiple model comparison analyses. The Stambaugh and Yuan (2016) four-factor model, which is the top performer in the time-series analyses, now takes the next place. Different from most studies in the time-series domain (see, for example, Fama and French, 1996, 2016; Hou, Xue, and Zhang, 2015, 2017a), I also find that the capital asset pricing model

of Sharpe (1964) and Lintner (1965) performs reasonably well. All of these findings remain robust irrespective of cross-sectional regression methodologies and normal and sequential tests for nonnested models.

Taken together, my statistical evidence from the cross-sectional analyses reinforces the argument of Barillas and Shanken (2017), Harvey and Liu (2017), and Kan and Robotti (2009) that the common practice of identifying the superior model(s) by informally comparing pricing performance metrics can lead to erroneous conclusions. Importantly, the empirical results in this chapter also contribute to the growing literature on assessing the performance of asset pricing models and have valuable implications for practical applications, including capital budgeting, equity valuation, quantitative investment management, and fund performance evaluation. For example, the Fama and French (1993) and Carhart (1997) four-factor model is the current workhorse model in evaluating mutual fund performance (see, among others, Ang, 2014; Fama and French, 2010; Fischer and Wermers, 2012). Given my cross-sectional statistical evidence on the superior performance of the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor and four-factor models, and the Barillas and Shanken (2018) six-factor model, all of them can be applied in this area.

The second chapter contributes to such exploratory investigation by developing a simple model of R&D venture, which offers a substantive insight into the R&D-return relation from the perspective of stock illiquidity. In the model, the firm conducting an R&D project generates a stochastic payoff after it successfully completes a number of sequential steps. The probability of success depends partly on the resources and efforts spent on the project and partly on experience or expertise gathered by the firm while traversing the time path of the project. During the course of the project, the firm faces the following trade-offs in allocating resources over time. On the one hand, if the firm currently spends a large amount of its resources to the R&D project, then it progresses faster along the steps towards its fruition and if successful, then the discounted value of the payoff from the R&D venture is larger. On the other hand, completing the project too early increases the probability of failure at an early stage because insufficient experience or knowledge is gathered by the firm over the shorter duration of the project. In addition, early completion of the R&D project increases expenses at the margin, since discounting of cash outflows renders costs incurred at a future date lower than costs incurred earlier.

In this environment, a firm that lacks sufficient internal funds to cover its R&D expenses but which anyway wishes to continue the project issues outside financial claims (i.e., new

public shares) at the beginning of the project to investors who may face liquidity problems at a later date before completion of the project. This implies that liquidity constrained investors may have to sell their stocks before they receive any payoff from the successful completion of the project. If the financial market is perfectly liquid and investors can sell their stocks instantaneously, then the problem is unlikely to arise. However, in the presence of asymmetric information due to the relatively unique nature of R&D activities (see, among others, Aboody and Lev, 2000), investors or dealers who are willing to buy such stocks may find it difficult to decipher whether this sale is triggered by a liquidity trader or by an informed trader selling upon receiving bad news (e.g., a failure of a drug under development to pass Phase I clinical tests). This translates into an illiquidity-induced increase in the R&D premium to outside investors, which in turn forces the firm to expedite project completion because of increased costs (i.e., due to illiquidity) associated with external equity financing. Moreover, this illiquidity-induced reduction of time for project completion increases the likelihood of its failure. As a result, the risk of R&D-intensive firm increases with stock illiquidity. To formalize this intuition and to motivate empirical analyses, I develop a new testable hypothesis, based on my theoretical model (see Section 2.2), that the positive relation between a firm's R&D investment and expected stock returns strengthens with the level of illiquidity.

I test my hypothesis both by Fama and MacBeth (1973) cross-sectional regressions and by independently double sorting stocks on illiquidity and R&D intensity. The cross-sectional regressions, which also control for the potential effects of size, book-to-market equity, short-term reversal, and momentum, confirm that the positive R&D-return relation is much stronger among illiquid stocks. The results remain qualitatively similar, when I conduct cross-sectional regression analyses using: the all-but-microcaps sample, which excludes stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution; industry dummies as additional control variables; subperiods; stock returns adjusted for delistings, following Shumway (1997); samples partitioned into high-tech firms and low-tech firms; alternative versions of the bid-ask spread; R&D intensity measured by R&D-to-total assets (i.e., R&D expenditure scaled by total assets); and the Amihud (2002) illiquidity measure. In a separate cross-sectional regression analysis, I also create interaction terms involving illiquidity dummy variables. After controlling for firm-level attributes, such as size, book-to-market equity, short-term reversal, and momentum, the results remain robust and support my theoretical model's prediction of a stronger R&D-return relation among illiquid stocks. For example, I find that, all else being equal, a one-standard

deviation increase in R&D-to-market ratio is associated with a 39 basis point higher future return per month for high illiquid stocks relative to all other stocks.

The model's prediction is also empirically supported by the results from an independent double-sorted portfolio analysis. Similar to the results from the Fama and MacBeth (1973) cross-sectional regressions, the positive R&D-return relation strengthens with the level of stock illiquidity. The R&D premium among illiquid stocks persists even after adjusting for risk using empirical factor pricing models such as the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model. In contrast, among stocks with low illiquidity, the high-minus-low R&D-to-market portfolio generates an insignificantly lower monthly return. Moreover, the average monthly abnormal returns on the portfolio relative to the three asset pricing models are much lower and statistically indistinguishable from zero at conventional levels. The empirical results, supporting my hypothesis, remain robust to using the all-but-microcaps sample, alternative measures of a firm's R&D intensity and stock illiquidity, and double-sorted quartile or quintile portfolios.

The third chapter studies the effect of product market competition on the positive relation between labor mobility and stock returns. Firms in industries employing workers whose labor skills are portable to other industries are more exposed to systematic risk than those in industries where workers have less portable skills (Donangelo, 2014). Since product market competition is identified as a source of increased return to skilled or industry-specific workforce and cost of employers, I conjecture product market competition sharpens the risk profile of firms in competitive industries than those in less competitive industries, if the firms have the same level of labor mobility. Therefore, the testable hypothesis is that the positive labor mobility-return relation is stronger among stocks in competitive industries. Namely, a higher market competition enhances or drives the relation between labor mobility and stock returns.

The hypothesis is tested by using both double-sorting portfolio analysis and Fama and MacBeth (1973) cross-sectional regressions. I find that the positive labor mobility-return relation is potentially driven by product market competition, in other words, a higher product market competition strengthens the positive relation. In my empirical analysis, I employ labor mobility estimate of Donangelo (2014) based on the level of interindustry dispersion of workers across occupations. For product market competition proxy, I use the Herfindahl-Hirschman Index (HHI) of Hou and Robinson (2006), which is commonly used in the litera-

ture on market competition (see, e.g., Hou and Robinson, 2006; Giroud and Mueller, 2011; Valta, 2012; Gu, 2016).

Firstly, I test my hypothesis by double sorting stocks on the ranked values of labor mobility and product market competition proxies. The results of sorted portfolio analysis confirm that the positive labor mobility-return relation is stronger among stocks in competitive industries. For instance, the value-weighted excess return of the high-minus-low labor mobility portfolio is significant for stocks in High competition group (competitive industries), but the significant high-minus-low portfolio return does not hold for stocks in the Low competition group (concentrated industries). The abnormal returns provided by the Ferson and Schadt (1996) conditional-CAPM, the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model document the same pattern. Additionally, I also double sort stocks by using the all-but-microcaps sample and provide equal-weighted portfolio returns, and the findings are consistent with the aforementioned results.

In the Fama and MacBeth (1973) regression analysis, the results document that the positive labor mobility-return relation only significantly exists among stocks in competitive industries. Firstly, I sort stocks into three groups based on the ranked value of product market competition proxy, and then run the Fama-MacBeth regression on labor mobility with four common risk characteristics (short-term reversal, momentum, book-to-market, and size). The results show that the coefficient of labor mobility is significantly higher for stocks in competitive industries. Secondly, I create interaction terms involving dummy variables, which the dummy variables are created based on the ranked value of product market competition proxy and the interaction terms are labor mobility estimate multiplies the dummy variables, and add the interaction terms and dummy variables into Fama-MacBeth regressions. The results show that the positive labor mobility-return relation increases with product market competition. The results simply indicate that the labor mobility has no significant effect on future stock returns among stocks in concentrated industries, since the summation to the coefficients of labor mobility and the interaction term is insignificant. The results are consistent with using the all-but-microcaps sample.

# Chapter 1

# Best of the best: A comparison of factor models

## 1.1 Introduction

Starting with the classic capital asset pricing model of Sharpe (1964) and Lintner (1965), the finance literature has been in search for a model that explains the cross-section of expected returns on assets. This had led to the development of a wide variety of factor pricing models in recent years. Although all of these models are merely approximations of reality (Barillas and Shanken, 2018; Gospodinov, Kan, and Robotti, 2013; Kan and Robotti, 2009; Kan, Robotti, and Shanken, 2013), it is important from an academic and practitioner perspective to know which model provides the best overall description of asset returns. For example, there is ample evidence, both empirical and anecdotal, that portfolio managers most often use the capital asset pricing model and a variety of multifactor models to compute expectations of returns (see, among others, Ang, 2014; Brealey, Myers, and Allen, 2016; Fischer and Wermers, 2012; Gitman and Mercurio, 1982; Graham and Harvey, 2001; Grinold and Kahn, 1995; Jagannathan and Meier, 2002). In this connection, Fama and French (2016) compare the performance of the recently proposed five-factor model of Fama and French (2015) and models that use subsets of its factors. Along this line of research, Hou, Xue, and Zhang (2017a) and Stambaugh and Yuan (2016) also investigate the performance of several prominent asset pricing models. All of these papers examine the relative performance of factor pricing models in time-series regressions using various test asset portfolios, but without the use of any formal statistical procedure that takes into account the sampling and model misspecification uncertainty. However, Barillas and Shanken (2017), Harvey and Liu (2017), Kan and Robotti (2009), and Kan, Robotti, and Shanken (2013), among others, emphasize that the practice of identifying the best model(s) simply by comparing point estimates of pricing performance metrics can be misleading.

In this chapter, I go beyond the vast majority of empirical studies by statistically comparing the performance of a much larger array of both classic and new-generation asset pricing models in explaining several prominent return anomalies. My array comprises the capital asset pricing model of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor model, the Asness and Frazzini (2013) three-factor model, the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the "high minus low" value factor, the Stambaugh and Yuan (2016) four-factor model, and the Barillas and Shanken (2018) six-factor model. Although recent research (see Harvey, Liu, and Zhu, 2016; McLean and Pontiff, 2016) documents hundreds of potential traded and nontraded factors that explain the cross-section of stock returns, I limit myself to these traded factor models for two reasons. First, these models have survived as the prominent if not the best models over the years. Importantly, most of my chosen models are frequently used for risk-adjustment purposes in the empirical asset pricing literature (see, for example, Bali, Cakici, and Whitelaw, 2011; Bali, Engle, and Murray, 2016; Gu, 2016; Hirshleifer, Hsu, and Li, 2017; Kuehn, Simutin, and Wang, 2017). Second, focusing only on return factor models allows us to explore their performance in both the time-series and the cross-sectional domains. Moreover, given the plethora of models, investigating the ten prominent factor models keeps the model comparison exercise at a reliably manageable level. Hence, my empirical examination of the relative model performance can be viewed as a search for the best of the best factor pricing models.

As in many recent papers (see, among others, Fama and French, 2015, 2016, 2017; Hou, Karolyi, and Kho, 2011; Hou, Xue, and Zhang, 2015, 2017a; Stambaugh and Yuan, 2016), I begin by applying my chosen factor models to the data and informally comparing them using a comprehensive set of pricing performance metrics estimated in the time-series domain. I then employ the pairwise test for equality of cross-sectional regression $R^2$s introduced by Kan, Robotti, and Shanken (2013). A key advantage of the sample cross-sectional $R^2$ test is that the testing procedure takes into account the impact of potential model misspecification and therefore ensures robust and valid statistical inference regarding relative performance. This also enables us to see how different are my informal findings on relative model performance in the time-series domain from those of the cross-sectional statistical evidence. However, the pairwise model comparison may not always determine unambiguously the best factor model when multiple models are involved in the horse race (Barillas, Kan, Robotti, and Shanken,

2017; Gospodinov, Kan, and Robotti, 2013; Kan, Robotti, and Shanken, 2013). To address this concern, I also conduct a multiple model comparison, following Kan, Robotti, and Shanken (2013), which identifies whether a "benchmark" asset pricing model significantly outperforms a set of alternative models in terms of the cross-sectional regression $R^2$.

To investigate the strengths and weaknesses of competing factor pricing models, choosing among test assets based on numerous predictive signals (see, for example, Green, Hand, and Zhang, 2014) is a challenge. In this regard, I follow prior empirical studies (see, among others, Fama and French, 1997, 2008, 2016; Feng, Giglio, and Xiu, 2017; Kan, Robotti, and Shanken, 2013; Kozak, Nagel, and Santosh, 2017; Stambaugh and Yuan, 2016), especially the suggestion of Lewellen, Nagel, and Shanken (2010), while keeping my analyses parsimonious. I choose subsets of test assets representative of major anomaly categories, such as investment, profitability, intangibles, and trading frictions, documented in the literature (see Green, Hand, and Zhang, 2014; Hou, Xue, and Zhang, 2015, 2017a,b, and references therein). Specifically, the sets of test assets used in this chapter are the value-weighted monthly excess returns on: the 25 size-STR (short-term reversal) portfolios, the 25 size-CI (abnormal capital investment) portfolios, the 25 size-DR (distress risk) portfolios, the 25 size-$\beta$ (market beta) portfolios, the 35 size-NI (net share issues) portfolios, the 25 size-MAX (lottery demand) portfolios, the 25 size-RVar (residual variance) portfolios, the 25 size-AC (accruals) portfolios, the 30 IND (industry) portfolios, and the 8 D10$-$1 (high minus low decile) portfolios. These test asset portfolios capture a vast cross-section of return anomalies; at the same time, a majority of them are readily available in the public domain, as described in the next section. More importantly, many of my test asset portfolios pose a greater challenge to existing asset pricing models (see, for example, Fama and French, 2016). Different from Hou, Xue, and Zhang (2017a) and Stambaugh and Yuan (2016), my rationale for using the eight sets of independent two-way sorted portfolios is that they allow us to see how well the competing factor models accommodate anomaly returns across size groups. In fact, asset pricing models have systematic problems explaining average returns on small stocks (see Fama and French, 1993, 1996, 2015, 2016, 2017).

My time-series analyses using point estimates of an exhaustive set of pricing performance measures demonstrate that the Stambaugh and Yuan (2016) four-factor model is the overall winner among all the asset pricing models in explaining anomalies. For example, the model outperforms, though informally, the competing models by producing the smallest point estimates for the average absolute alpha and a variant of the alpha dispersion metric in half of the sets of test asset portfolios. Considering the metric measuring the dispersion (second

moment) of the alphas due to sampling error, I see that the Stambaugh and Yuan (2016) four-factor model delivers the largest point estimate in four out of the ten sets of test portfolios. Moreover, the model generates the least number of statistically significant alphas for six portfolio sets. The Hou, Xue, and Zhang (2015) $q$-factor model does a reasonably good job in accommodating anomaly returns and takes second place in the horse race. For example, the $q$-factor model produces insignificant alphas for all 25 of the size-DR portfolios. The model also offers the largest point estimate for the dispersion (second moment) of the alphas, due to sampling error, in three sets of test asset portfolios. Among the remaining competing models, the Fama and French (2015) five-factor model and the Barillas and Shanken (2018) six-factor model perform about equally well and take equal third place. Both of them deliver the largest point estimate for the average time-series regression $R^2$ in five out of the ten sets of portfolios. Looking at the 42 small size portfolios across the eight anomaly variables, I find that all of my asset pricing models have difficulties explaining their returns – an observation consistent with prior studies.

When the model comparison exercises are carried out based on pairwise tests of equality of sample cross-sectional $R^2$s and multiple model comparison tests, a different but statistically valid picture emerges. Overall, I find that the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, and the Barillas and Shanken (2018) six-factor model, all perform about equally well, and so jointly take first place in the horse race. More importantly, these asset pricing models are never statistically dominated at the 5% level in any of my multiple model comparison analyses. The Stambaugh and Yuan (2016) four-factor model, which is the top performer in the time-series analyses, now takes the next place. Different from most studies in the time-series domain (see, for example, Fama and French, 1996, 2016; Hou, Xue, and Zhang, 2015, 2017a), I also find that the capital asset pricing model of Sharpe (1964) and Lintner (1965) performs reasonably well. All of these findings remain robust irrespective of cross-sectional regression methodologies and normal and sequential tests for nonnested models.

Taken together, my statistical evidence from the cross-sectional analyses reinforces the argument of Barillas and Shanken (2017), Harvey and Liu (2017), and Kan and Robotti (2009) that the common practice of identifying the superior model(s) by informally comparing pricing performance metrics can lead to erroneous conclusions. Importantly, the empirical results in this chapter also contribute to the growing literature on assessing the performance of asset pricing models and have valuable implications for practical applications, including capital

budgeting, equity valuation, quantitative investment management, and fund performance evaluation. For example, the Fama and French (1993) and Carhart (1997) four-factor model is the current workhorse model in evaluating mutual fund performance (see, among others, Ang, 2014; Fama and French, 2010; Fischer and Wermers, 2012). Given my cross-sectional statistical evidence on the superior performance of the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor and four-factor models, and the Barillas and Shanken (2018) six-factor model, all of them can be applied in this area.

This chapter differs from several recent papers that compare model performance, as I employ misspecification robust statistical tests on a much larger array of factor pricing models in the cross-sectional domain. Some of these papers include Fama and French (2016), Hou, Xue, and Zhang (2017a), and Stambaugh and Yuan (2016). For instance, Fama and French (2016) show that the five-factor model of Fama and French (2015) accommodates several return anomalies not explained by the Fama and French (1993) three-factor model. But the authors compare the performance of the Fama and French (2015) five-factor model only with that of models that use subsets of those same five factors. Stambaugh and Yuan (2016) compare the performance of their version of the four-factor model with that of only three other models, namely the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, and the Hou, Xue, and Zhang (2015) $q$-factor model. Using one-way (univariate) sorted anomaly portfolios in the time-series regressions, the authors show that their four-factor model, also known as the mispricing factor model, performs the best. Likewise, Hou, Xue, and Zhang (2017a) show that the $q$-factor model of Hou, Xue, and Zhang (2015) outperforms the Fama and French (2015) five-factor model in explaining a wide array of asset pricing anomalies. However, their list of models in the horse race excludes the newly proposed four-factor model of Stambaugh and Yuan (2016). More recently, Barillas and Shanken (2018) develop a Bayesian framework for comparing return factor models in terms of their posterior probabilities. But it requires formulating priors on the pricing errors and therefore empirical results can be sensitive. In this context, the pairwise cross-sectional $R^2$ equality test of Kan, Robotti, and Shanken (2013) that I use in this chapter is much simpler to implement where both traded and nontraded factor pricing models can be evaluated and allows for fairly reliable statistical inferences to be drawn. Finally, Barillas, Kan, Robotti, and Shanken (2017) compare eight asset pricing models based on their maximum squared Sharpe ratios. But my model comparison analyses utilizing return anomalies also show the strengths and weaknesses of the ten prominent asset pricing models.

The remainder of this chapter is organized as follows. Section 1.2 describes the factor

pricing models, the sets of return anomaly portfolios that are used as test assets, and the metrics for comparing model performance in explaining these anomalies. Section 1.3 discusses the results from the time-series regressions, while Section 1.4 summarizes the results from the cross-sectional regressions. Finally, Section 1.5 concludes this chapter. A separate Appendix contains further details on test assets, robustness tests, and additional results.

## 1.2 Factor models and anomaly portfolios

### 1.2.1 Competing models

I examine the ability of ten different factor pricing models to explain the average excess returns of portfolios sorted on several well-known anomaly variables. These models are: (1) the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), which includes only a market factor; (2) the Fama and French (1993) three-factor (FF3) model, which extends the CAPM by including empirically motivated size and value factors; (3) the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, which adds a momentum factor to the FF3 model; (4) the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model, which combines a traded liquidity factor with those of the FF3 model; (5) the Asness and Frazzini (2013) three-factor (FFAF) model, which adds a more "timely" version of the value factor to the market and size factors of the FF3 model; (6) the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model, comprising market, size, investment, and profitability factors; (7) the Fama and French (2015) five-factor (FF5) model, consisting of market, size, value, profitability, and investment factors; (8) the four-factor (FF4) model, which drops the value factor of the FF5 model; (9) the Stambaugh and Yuan (2016) four-factor (SY4) model, which comprises market, size, and two mispricing factors; and (10) the Barillas and Shanken (2018) six-factor (BS6) model, comprising the market, size, and momentum factors of the FF5 model, the profitability and investment factors of the HXZ model, and the value factor of the FFAF model. The time-series regression specifications of

these factor models are as follows:

$$r^e_{i,t} = \alpha_{i,\text{CAPM}} + \beta_{i,\text{MKT}}\text{MKT}_t + \epsilon_{i,t}, \tag{1.1}$$

$$r^e_{i,t} = \alpha_{i,\text{FF3}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}^*}\text{SMB}^*_t + \beta_{i,\text{HML}}\text{HML}_t + \epsilon_{i,t}, \tag{1.2}$$

$$r^e_{i,t} = \alpha_{i,\text{FFC}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}^*}\text{SMB}^*_t + \beta_{i,\text{HML}}\text{HML}_t + \beta_{i,\text{UMD}}\text{UMD}_t + \epsilon_{i,t}, \tag{1.3}$$

$$r^e_{i,t} = \alpha_{i,\text{FFPS}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}^*}\text{SMB}^*_t + \beta_{i,\text{HML}}\text{HML}_t + \beta_{i,\text{LIQ}}\text{LIQ}_t + \epsilon_{i,t}, \tag{1.4}$$

$$r^e_{i,t} = \alpha_{i,\text{FFAF}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}^*}\text{SMB}^*_t + \beta_{i,\text{HML}^m}\text{HML}^m_t + \epsilon_{i,t}, \tag{1.5}$$

$$r^e_{i,t} = \alpha_{i,\text{HXZ}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{ME}}r_{\text{ME},t} + \beta_{i,\text{I/A}}r_{\text{I/A},t} + \beta_{i,\text{ROE}}r_{\text{ROE},t} + \epsilon_{i,t}, \tag{1.6}$$

$$r^e_{i,t} = \alpha_{i,\text{FF5}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}}\text{SMB}_t + \beta_{i,\text{HML}}\text{HML}_t + \beta_{i,\text{RMW}}\text{RMW}_t + \beta_{i,\text{CMA}}\text{CMA}_t + \epsilon_{i,t}, \tag{1.7}$$

$$r^e_{i,t} = \alpha_{i,\text{FF4}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}}\text{SMB}_t + \beta_{i,\text{RMW}}\text{RMW}_t + \beta_{i,\text{CMA}}\text{CMA}_t + \epsilon_{i,t}, \tag{1.8}$$

$$r^e_{i,t} = \alpha_{i,\text{SY4}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}_M}\text{SMB}_{M,t} + \beta_{i,\text{MGMT}}\text{MGMT}_t + \beta_{i,\text{PERF}}\text{PERF}_t + \epsilon_{i,t}, \tag{1.9}$$

$$r^e_{i,t} = \alpha_{i,\text{BS6}} + \beta_{i,\text{MKT}}\text{MKT}_t + \beta_{i,\text{SMB}}\text{SMB}_t + \beta_{i,\text{I/A}}r_{\text{I/A},t} + \beta_{i,\text{ROE}}r_{\text{ROE},t} + \beta_{i,\text{HML}^m}\text{HML}^m_t + \beta_{i,\text{UMD}}\text{UMD}_t + \epsilon_{i,t}, \tag{1.10}$$

where $r^e_{i,t} = r_{i,t} - r_{f,t}$ is the period $t$ return on asset $i$ in excess of the risk-free rate; $\text{MKT}_t$, $\text{SMB}^*_t$ (small minus big), and $\text{HML}_t$ (high minus low) are, respectively, the market, size, and value factors of Fama and French (1993); $\text{LIQ}_t$ is the traded liquidity factor of Pástor and Stambaugh (2003); $\text{HML}^m_t$ is the value factor of Asness and Frazzini (2013); $r_{\text{ME},t}$, $r_{\text{I/A},t}$, and $r_{\text{ROE},t}$ are, respectively, the size, investment, and profitability factors of Hou, Xue, and Zhang (2015); $\text{SMB}_t$, $\text{RMW}_t$ (robust minus weak), $\text{CMA}_t$ (conservative minus aggressive), and $\text{UMD}_t$ (up minus down) are, respectively, the size, profitability, investment, and momentum factors of Fama and French (2015, 2016); and $\text{SMB}_{M,t}$, $\text{MGMT}_t$, and $\text{PERF}_t$ are the size and two mispricing factors of Stambaugh and Yuan (2016), respectively.

Before proceeding to the factor model regression analyses in the subsequent sections, I now briefly describe the factors of interest. Fama and French (1993) construct the market factor, MKT, as the return on the value-weighted portfolio of all US-based common stocks in the Center for Research in Security Prices database minus the one-month Treasury bill rate from Ibbotson Associates. The SMB* and HML factors come from independent $2 \times 3$ sorts of stocks on size (i.e., equity market capitalization) and book-to-market equity ratio (B/M). The intersections of the two size and three B/M groups produce six value-weighted portfolios. The original size factor, SMB*, is the average of the returns on the three small

stock portfolios minus the average of the returns on the three big stock portfolios. The value factor, HML, is the average of the returns on the two high B/M portfolios minus the average of the returns on the two low B/M portfolios. Adopting a seemingly small modification to the HML value factor of the FF3 model, Asness and Frazzini (2013) construct a more "timely" version of the value factor, denoted $\text{HML}^m$, based on B/M rankings that use the most recent monthly stock price in the denominator.

Pástor and Stambaugh (2003) sort stocks into deciles of liquidity risk exposure estimate and construct their liquidity factor, LIQ, as the difference in value-weighted returns between the top and bottom decile portfolios. The excess return factors constructed by Hou, Xue, and Zhang (2015) use independent $2 \times 3 \times 3$ sorts of stocks on size, investment measured by investment-to-assets ratio (I/A), and profitability measured by return on equity (ROE). The intersections of the two size, three I/A, and three ROE groups produce 18 value-weighted portfolios. The size factor, $r_{\text{ME}}$, is the average of the nine small stock portfolio returns minus the average of the nine big stock portfolio returns. The investment factor, $r_{\text{I/A}}$, is the average of the six low I/A portfolio returns minus the average of the six high I/A portfolio returns. Similarly, the profitability factor, $r_{\text{ROE}}$, is the average of the returns on the six high ROE portfolios minus the average of the returns on the six low ROE portfolios. A feature of these excess return factors that distinguishes them from those of other asset pricing model factors is that they are constructed using stocks of nonfinancial firms with a nonnegative B/M only.

Departing from the original size factor SMB* of the FF3 model, Fama and French (2015, 2016) construct their size factor SMB as the average of the value-weighted returns on the nine small stock portfolios of the three independent $2 \times 3$ sorts minus the average of the value-weighted returns on the nine big stock portfolios. The profitability, investment, and momentum factors are, respectively, from independent $2 \times 3$ sorts of stocks on size and operating profitability (OP), independent $2 \times 3$ sorts of stocks on size and investment (Inv) measured by asset growth, and independent $2 \times 3$ sorts of stocks on size and momentum, denoted MOM (measured as the cumulative average return over the past 12 months, skipping the most recent month's return). In each case, the intersections of the sorts produce six value-weighted portfolios. The profitability factor RMW is then the average of the returns on the two high OP portfolios minus the average of the returns on the two low OP portfolios. Likewise, CMA is the average of the two low Inv portfolio returns minus the average of the two high Inv portfolio returns. The momentum factor, UMD, is the average of the two up (i.e., high value of MOM) portfolio returns minus the average of the two down (i.e., low value of MOM) portfolio returns. Fama and French (2015, 2016) show that their value

factor, HML, is redundant in explaining the cross-section of average US stock returns. We, therefore, include the FF4 model, on the grounds of parsimony.[1] It is worth highlighting that although the FF4 model includes return factors that are designed to capture risk premiums similar to those of factors in the HXZ model, the factor constructions are very different in these models. For example, the profitability factor $r_{\text{ROE}}$ is from monthly sorts on ROE, whereas RMW is from annual sorts on OP.

Stambaugh and Yuan (2016) introduce two mispricing factors from a set of 11 prominent return anomalies documented in the literature (see, for example, Stambaugh, Yu, and Yuan, 2015). The first mispricing factor, denoted MGMT, makes use of information from a cluster of anomaly variables, including NI, composite equity issues, AC, net operating assets, asset growth, and I/A. The second mispricing factor, PERF, comes from another cluster of anomalies, comprising financial distress, $O$-score bankruptcy probability, momentum, gross profitability, and return on assets. Specifically, the authors construct two composite mispricing measures, P1 and P2, on a monthly basis for each stock by averaging its rankings with respect to the anomaly measures within each of the aforementioned clusters. Their next step entails the formation of six value-weighted portfolios from independent $2 \times 3$ sorts of stocks on market capitalization and a composite mispricing measure P1. The authors repeat the two-way sorting except the second sort is on the composite mispricing measure P2. The mispricing factor MGMT, related to firm management, is then the average of the two low P1 (underpriced) portfolio returns minus the average of the two high P1 (overpriced) portfolio returns. The other mispricing factor, PERF, which is related more to firm performance, is the average of the returns on the two low P2 portfolios minus the average of the returns on the two high P2 portfolios. In addition to these factors, Stambaugh and Yuan (2016) construct their version of the size factor, denoted $\text{SMB}_M$, using stocks that are least likely to be mispriced. Notably, the size factor $\text{SMB}_M$ in a given month consists of stocks that are not used in forming either of the mispricing factors. As a result, the construction of $\text{SMB}_M$ differs significantly from that of the SMB* and SMB factors.

I source data on the risk-free rate, and the MKT, SMB*, SMB, HML, UMD, RMW, and CMA factors from the Internet Data Library maintained by Kenneth R. French.[2] The data on the $r_{\text{ME}}$, $r_{\text{I/A}}$, and $r_{\text{ROE}}$ factors are obtained from Lu Zhang's website,[3] while the

[1] Xing (2008) introduces an investment growth factor and shows that the pricing factor contains information similar to that of the HML factor. Recently, Hou, Xue, and Zhang (2015) claim that the value factor HML is a noisy version of their investment factor $r_{\text{I/A}}$.

[2] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[3] See https://sites.google.com/site/theqfactormodel/?pli=1.

data on the LIQ factor are from Ľuboš Pástor's website.[4] I collect data on the size factor $SMB_M$ and the two mispricing factors, MGMT and PERF, from Yu Yuan's website.[5] The data on the alternative version of the value factor, $HML^m$, are sourced from the AQR Data Library.[6] Finally, my sample period spans January 1968 to December 2016. To conserve space, I provide factor correlations in Table 1.A1 of the Appendix.

### 1.2.2 Anomaly portfolios

To identify the strengths and weaknesses of the asset pricing models, I make use of several prominent return anomalies targeted in prior studies (see Bali, Cakici, and Whitelaw, 2011; Fama and French, 1997, 2016, 2017; Feng, Giglio, and Xiu, 2017; Hou, Xue, and Zhang, 2017a; Kozak, Nagel, and Santosh, 2017; Linnainmaa and Roberts, 2016). The list comprises STR (see Lehmann, 1990; Jegadeesh, 1990), CI (see Titman, Wei, and Xie, 2004), DR (see Bharath and Shumway, 2008; Campbell, Hilscher, and Szilagyi, 2008), market $\beta$ (see Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973; Frazzini and Pedersen, 2014), NI (see Ikenberry, Lakonishok, and Vermaelen, 1995; Loughran and Ritter, 1995), MAX (see Bali, Cakici, and Whitelaw, 2011), RVar (see Ang, Hodrick, Xing, and Zhang, 2006; Fu, 2009), and AC (see Sloan, 1996). My test assets are from independent two-way sorts of NYSE-, AMEX-, and NASDAQ-listed ordinary common stocks on size and each of the return anomaly variables from the above list. Specifically, the sets of test assets used in the empirical analyses include the value-weighted monthly excess returns on the 25 size-STR portfolios, the 25 size-CI portfolios, the 25 size-DR portfolios, the 25 size-$\beta$ portfolios, the 35 size-NI portfolios, the 25 size-MAX portfolios, the 25 size-RVar portfolios, and the 25 size-AC portfolios. As a further assessment of my factor pricing models, I make use of the value-weighted monthly excess returns on the 30 IND (see Fama and French, 1997) portfolios and the 8 D10−1 portfolios associated with one-way sorts on STR, CI, DR, market $\beta$, NI, MAX, RVar, and AC.[7] The inclusion of all these return anomaly portfolios is also in line with the advice of Lewellen, Nagel, and Shanken (2010) to improve the power of asset pricing tests by considering portfolios, in the test assets, that are sorted on market $\beta$, industry, or other firm-level characteristics.

The majority of my test assets are two-way independent sorted portfolios. The rationale is that they allow us to examine both the variation in anomaly returns and the explanatory

[4] See http://faculty.chicagobooth.edu/lubos.pastor/research/.
[5] See http://www.saif.sjtu.edu.cn/facultylist/yyuan/.
[6] See https://www.aqr.com/library/data-sets/the-devil-in-hmls-details-factors-monthly.
[7] To conserve space, I omit definitions of the anomaly variables and details of the portfolio construction in this chapter. These are available in Fama and French (2008, 2016) and in the Appendix.

power of the different factor pricing models across size groups. In fact, anomaly patterns are much stronger for small (microcap) stocks and all the workhorse asset pricing models in the literature have systematic problems in explaining their average excess returns (Fama, 1998; Fama and French, 2012, 2015, 2016, 2017). Moreover, my rationale for using the value-weighted portfolio excess returns follows from Fama (1998), who argues that value-weighting more accurately captures the total wealth effects experienced by investors. I source data on STR, market $\beta$, NI, RVar, AC, and IND portfolio returns once again from Kenneth R. French's website. The data sources of the remaining anomaly portfolio returns are provided in the Appendix.

### 1.2.3 Model performance measures

My assessment of the performance of each return factor model in the time-series regressions is based on a battery of metrics commonly used in the empirical asset pricing literature (see Fama and French, 1993, 2015, 2016, 2017; Hou, Xue, and Zhang, 2015, 2017a; Stambaugh and Yuan, 2016). The first metric is the $F$-statistic of the Gibbons, Ross, and Shanken (1989) test, henceforth denoted GRS statistic. The null hypothesis states that the cross-section of alphas (i.e., all intercepts in time-series regressions of test assets on a return factor model) are jointly indistinguishable from zero. Although popular in the literature, the Gibbons, Ross, and Shanken (1989) test is not without shortcomings. For example, the power of the test decreases with the number of assets. The second metric used to evaluate competing factor models is the average absolute value of the alphas, denoted $A|\alpha_i|$. In the time-series factor regression, alpha is viewed as a measure of model mispricing or a test asset's deviation from the model. My third metric, $A|\alpha_i|/A|\overline{r}_i|$, is the ratio of the average absolute value of the alphas to the average absolute value of $\overline{r}_i$. I compute $\overline{r}_i$ as the average excess return on an anomaly portfolio $i$ minus the value-weighted average excess return on the market portfolio. The fourth metric that I employ is $A\alpha_i^2/A\overline{r}_i^2$, which is the ratio of the average squared alpha to the average squared value of $\overline{r}_i$. Both $A|\alpha_i|/A|\overline{r}_i|$ and $A\alpha_i^2/A\overline{r}_i^2$ measure the dispersion of the alphas produced by a given asset pricing model relative to the dispersion of average excess returns on test assets. Consequently, low values of these ratios indicate better performance of the model. My fifth metric for model performance evaluation is $As^2(\alpha_i)/A\alpha_i^2$, which is the ratio of the average variance estimate of the sampling errors of the estimated alphas to $A\alpha_i^2$. More precisely, $As^2(\alpha_i)/A\alpha_i^2$ shows the proportion of the dispersion (second moment) of the alpha estimates that is due to sampling error rather than to dispersion of the true alphas. By construction, a higher value of the ratio suggests better

model performance. Another metric that I estimate is $A(R^2)$, which is the average value of the time-series regression $R^2$ adjusted for degrees of freedom.

I next compute two additional metrics as in Barillas and Shanken (2017) and Fama and French (2017). These are the maximum squared Sharpe ratio, denoted $Sh^2(\alpha)$, for the alphas of test assets relative to a given factor model and the maximum squared Sharpe ratio of a model's factor(s), denoted $Sh^2(f)$. The economic mispricing metric, $Sh^2(\alpha)$, is also known as the Sharpe ratio improvement metric. In fact, Gibbons, Ross, and Shanken (1989) show that

$$Sh^2(\alpha) = Sh^2(f, r^e) - Sh^2(f) = \alpha' \Sigma^{-1} \alpha, \tag{1.11}$$

where $r^e$ is the set of test asset (excess) returns, $f$ is the excess return factor(s) of a given model, $\alpha$ is the cross-section of alphas, $\Sigma$ is the time-series regression residual (invertible) covariance matrix, and $Sh^2(f, r^e)$ is the maximum squared Sharpe ratio of the ex post tangency portfolio formed by combining the test assets with the factor(s).[8] A lower value of $Sh^2(\alpha)$ implies a lower squared Sharpe ratio improvement from exploiting mispricing (nonzero alphas) by a given factor model, that is, better model performance. Fama and French (2017) note that the sample estimates of $Sh^2(f)$ are biased upward. Specifically, the bias is likely to be larger in smaller samples and for models with more traded factors. Hence, I also compute a bias-free version of the maximum squared Sharpe ratio of the factor(s), denoted $Sh^2_B(f)$, as the average of $Sh^2(f)$ from 100,000 full-sample bootstrap simulation runs. Harvey and Liu (2017), however, argue that a factor model might still do a poor job in explaining the cross-section of average returns even if it generates a large point estimate of $Sh^2(f)$.

Consistent with many recent papers in the empirical asset pricing literature (see, among others, Fama and French, 1996, 2015, 2016; Hou, Xue, and Zhang, 2015, 2017a; Stambaugh and Yuan, 2016; and references therein), I first compare the performance of different factor models informally, by simply eyeballing the point estimates of the above metrics. Barillas and Shanken (2017), however, show that identifying the superior model (or, equivalently, ranking models) based on such an informal, but common, procedure can be misleading. In this regard, Harvey and Liu (2017) also caution that when two competing factor models both generate nonzero alphas, the use of the GRS statistic to heuristically determine the

[8] Although a negative relation between $Sh^2(\alpha)$ and $Sh^2(f)$ is expected, the relation may not be perfect across different sets of test assets (Fama and French, 2017).

relative performance of the two models is inappropriate. Furthermore, in the excluded factor time-series regressions, the use of the Gibbons, Ross, and Shanken (1989) test is not suitable to make a valid statistical inference about comparison for nonnested models (Barillas and Shanken, 2017; Barillas, Kan, Robotti, and Shanken, 2017; Fama and French, 2017). Taking these important issues into account, I then examine whether a competing factor model is significantly better than another candidate model. To do so, I adopt the pairwise test for equality of cross-sectional regression $R^2$s introduced by Kan, Robotti, and Shanken (2013). The cross-sectional $R^2$ test, described in the following section, overcomes many of the issues with model comparisons that arise in the traditional alpha-based framework. In addition, this testing procedure accounts for the impact of potential model misspecification and therefore allows for robust and valid statistical inference. However, the pairwise model comparison is open to the criticism that the process of searching over alternative models can lead to an overstatement of statistical significance (Barillas, Kan, Robotti, and Shanken, 2017; Kan, Robotti, and Shanken, 2013). To address this issue, I also adopt the multiple model comparison test, which determines whether a given factor pricing model outperforms a set of alternative models in terms of the cross-sectional regression $R^2$.

### 1.2.4 Tests for comparing cross-sectional $R^2$s

#### 1.2.4.1 Pairwise tests of equality of cross-sectional $R^2$s

In this section, I briefly discuss the Kan, Robotti, and Shanken (2013) test of model comparison based on the second-pass cross-sectional regression $R^2$s of two asset pricing models.[9] Let $\rho_A^2$ and $\rho_B^2$ be the cross-sectional $R^2$s of two competing models $A$ and $B$, respectively. When models are nested, then statistically verifying whether they have the same explanatory power involves a test of $H_0$: $\rho_A^2 = \rho_B^2$. But the test of $H_0$: $\rho_A^2 = \rho_B^2$ is fairly complicated for models that are nonnested. This is due to three possible asymptotic distributions for $\widehat{\rho}_A^2 - \widehat{\rho}_B^2$ under the null hypothesis. First, it is possible that the pricing factors that are not common to the two nonnested models are irrelevant for explaining the cross-sectional variation in average (excess) returns. In this case, the models will have the same pricing errors and the same overall goodness of fit in the population. Second, the two models may produce different pricing errors but still have identical cross-sectional $R^2$s. Finally, it is also possible that the two nonnested models are both correctly specified (i.e., $\rho_A^2 = \rho_B^2 = 1$),

[9] The cross-sectional regression specification for a given factor model is

$$\mu_r^e = C\lambda,$$

where $\mu_r^e$ is the mean of $r^e$, $C = [1_N, cov[r^e, f']]$, $\lambda = (C'WC)^{-1}C'W\mu_r^e$, $W$ is the weighting matrix, and $N$ is the number of test assets. For more details, see Kan, Robotti, and Shanken (2013).

although their factors differ. Given the aforementioned three distinct possibilities, the test of $H_0$: $\rho_A^2 = \rho_B^2$ for nonnested models entails a complicated sequential procedure (described in the Appendix). An alternative to the sequential testing procedure is simply to perform the normal test of $H_0$: $0 < \rho_A^2 = \rho_B^2 < 1$. This approach implicitly rules out the possibility that the additional factors in each model are completely irrelevant for explaining the variation in average returns. More importantly, it assumes that both models are misspecified, since asset pricing models are merely approximations of the true data generating process (Kan, Robotti, and Shanken, 2013).

I, in this chapter, perform both the sequential test and the normal test when comparing nonnested models. But for brevity, I report only the results based on the normal test. The results based on the sequential test are provided in the Appendix Tables 1.A12 through 1.A21, which are qualitatively similar to those reported in this chapter. Moreover, I compute both the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s. The use of the OLS $R^2$ is more relevant if the focus is on explaining the average (excess) returns of test assets, while the use of the GLS $R^2$ is more relevant from an investment perspective (Kandel and Stambaugh, 1995; Kan, Robotti, and Shanken, 2013; Lewellen, Nagel, and Shanken, 2010).

#### 1.2.4.2 Multiple model comparison

I follow Kan, Robotti, and Shanken (2013) to conduct the multiple model comparison test. Let $\delta \equiv (\delta_2, \ldots, \delta_p)$, where $\delta_i \equiv \rho_1^2 - \rho_i^2$ for model $i = 2, \ldots, p$. I test the null hypothesis that the benchmark factor model 1, performs at least as well as the competing factor models 2 to $p$, that is, $H_0$: $\delta \geqslant 0_u$ with $u = p-1$. The alternative hypothesis is that some model has a higher population cross-sectional $R^2$ than the benchmark factor model 1. The multiple model comparison test is based on the sample counterpart of $\delta$, $\hat{\delta} \equiv (\hat{\delta}_2, \ldots, \hat{\delta}_p)$, where $\hat{\delta}_i \equiv \hat{\rho}_1^2 - \hat{\rho}_i^2$. I assume that $0 < \rho_i^2 < 1$ for all model $i$, so that $\hat{\delta}$ has an asymptotically normal distribution with mean $\delta$ and covariance matrix $\Sigma_{\hat{\delta}}$. The test statistic is then constructed by solving the following quadratic programing problem:

$$\min_{\delta} (\hat{\delta} - \delta)' \hat{\Sigma}_{\hat{\delta}}^{-1} (\hat{\delta} - \delta) \quad \text{s.t.} \quad \delta \geqslant 0_u, \tag{1.12}$$

where $\hat{\Sigma}_{\hat{\delta}}$ is a consistent estimator of $\Sigma_{\hat{\delta}}$. The likelihood ratio test of the null hypothesis is

$$\text{LR} = T(\hat{\delta} - \tilde{\delta})' \hat{\Sigma}_{\hat{\delta}}^{-1} (\hat{\delta} - \tilde{\delta}), \tag{1.13}$$

where $\tilde{\delta}$ is the optimal solution to the problem given by equation (1.12). To conduct statistical inferences, I obtain asymptotically valid $p$-values following a numerically efficient procedure outlined in Kan, Robotti, and Shanken (2013).

For the multiple nonnested model comparison, I first remove those alternative factor pricing models $i$ that are nested by the benchmark model. If any of the remaining alternatives is nested by another alternative factor model, I remove the "smaller" model. Finally, I also remove any alternative models that nest the benchmark factor model. But to conduct the nested multiple model comparison, I cannot use the likelihood ratio test, since $\hat{\delta}$ is not asymptotically normally distributed. In this case, I form a single expanded model, which includes all of the factors contained in the models nesting the benchmark model. Hence, the null hypothesis that the benchmark model has the same OLS (GLS) cross-sectional regression $R^2$ as these alternative models can be tested using the approach for pairwise nested model comparison in Section 1.2.4.1.

## 1.3 Time-series results

Table 1.1 presents the factor model performance in the time-series (absolute) tests on the different sets of anomaly portfolios. To save space, I provide average monthly excess returns and alphas for portfolios, relative to each of the models, and the associated Newey and West (1987) adjusted $t$-statistics in Tables 1.A2 through 1.A11 of the Appendix.[10] Throughout this section, my discussion focuses on the best-performing asset pricing model.

### 1.3.1 Size-STR (short-term reversal) portfolios

Starting with the 25 size-STR portfolios in Panel A of Table 1.1, I find that all the models are comfortably rejected by the Gibbons, Ross, and Shanken (1989) test at conventional significance levels. The $p$-values corresponding to the GRS statistics for models round to zero to at least three decimal places. But the BS6 model outperforms, though not statistically, all other factor models, as it generates the smallest point estimate of the GRS statistic. The next best asset pricing model turns out to be the HXZ model, followed by the FF5 model. The point estimate of the GRS statistic generated by the FF4 model is marginally higher than those of the HXZ and FF5 models. The SY4 model appears to be the worst-performing model, followed by the FFPS model, in terms of the magnitude of the GRS statistic. The average absolute value of 0.144% per month for alphas in the FFAF model is the smallest

[10] Standard in the literature, I consider an alpha to be statistically significant if the corresponding $t$-statistic is at least 2.

among all the factor pricing models. The value of 0.599 for the ratio $A|\alpha_i|/A|\overline{r}_i|$ produced by the FFAF model is also the smallest among all the competing models. A point estimate of 0.599 for $A|\alpha_i|/A|\overline{r}_i|$ implies that the dispersion of alphas is about 60% as large as the dispersion of average excess returns on my anomaly portfolios. The BS6 model appears to be the top performer when looking at the point estimate of 0.531 for the ratio $A\alpha_i^2/A\overline{r}_i^2$, which is the smallest among all the competing factor models. In terms of the magnitude of $A(R^2)$, the BS6 model once again turns out to be the best-performing asset pricing model, followed by the FFC model, while the CAPM is the worst performer, followed jointly by the FF3, FFPS, and HXZ models.

I notice that almost all of the models outperform the CAPM by generating lower point estimates for $A|\alpha_i|$ and $A|\alpha_i|/A|\overline{r}_i|$ metrics. But the point estimate of the ratio $As^2(\alpha_i)/A\alpha_i^2$ for the CAPM tells a different story. For example, about 24% of the dispersion (second moment) of the alpha estimates for the CAPM is due to sampling error, whereas it is only about 10% for the SY4 model. Notably, about 18% of the second moment of the alpha estimates for the BS6 model is due to sampling error and the remaining 82% is due to dispersion in the true alphas. But the six factors of the model generate the largest point estimates of 0.237 and 0.147, respectively, for $Sh^2(f)$ and $Sh_B^2(f)$. The SY4 model factors also perform well, generating a large $Sh^2(f)$ of 0.233. When it comes to $Sh^2(\alpha)$, the FF4 model produces the smallest point estimate of 0.685. A common finding with the $Sh^2(f)$ metric is that, after adjusting for upward bias, the point estimates of $Sh_B^2(f)$ drop by as much as 52% (see, for example, the SY4 model).

In Table 1.A2 of the Appendix, all models generate a statistically significant alpha for the microcap extreme STR portfolio. This result shows that microcap extreme STR stocks are a huge problem for the asset pricing models. In the smallest size quintile, all but the FFC, HXZ, SY4, and BS6 models generate a statistically significant alpha for only one portfolio, which is the lowest number across all models. I also notice that the BS6 model outperforms other models in explaining average excess returns, by generating only five significant alphas. In contrast, both the FFC and the SY4 models generate 11 significant alphas for portfolios, which is the highest number across all the factor models. To sum up, the point estimates of more than half of the performance metrics favor the BS6 model as the best asset pricing model.

### 1.3.2 Size-CI (abnormal capital investment) portfolios

I now focus on the 25 size-CI portfolios in Panel B of Table 1.1. The Gibbons, Ross, and Shanken (1989) test easily rejects all the asset pricing models. But the rejection is the weakest for the FF4 model, which generates a GRS statistic of 1.981 ($p$-value = 0.003). In contrast, the FFC model produces the largest GRS statistic of 3.011 ($p$-value = 0.000). I find that the average absolute alpha produced by the FFPS model is only 0.079% per month, the smallest among all the competing factor models. The CAPM generates the largest point estimate for $A|\alpha_i|$, which is 0.183% per month. When looking at the two dispersion measures of alphas, $A|\alpha_i|/A|\overline{r}_i|$ and $A\alpha_i^2/A\overline{r}_i^2$, I find that the FFPS and FF3 models generate the smallest values, of 0.323 and 0.121, respectively. The FF3 model also produces the largest point estimate of the ratio $As^2(\alpha_i)/A\alpha_i^2$, which is 0.660. This indicates that two-thirds of the second moment of the alpha estimates for the model is due to sampling error and only one-third is due to dispersion in the true alphas. I further notice that the BS6 model produces the largest point estimate for $A(R^2)$, which is about 90%. But in terms of the magnitude of $Sh^2(\alpha)$, the FF4 model is the best performer, generating the smallest value for the metric among all the asset pricing models.

When examining the alphas in the Appendix Table 1.A3, I see that the BS6 model generates a statistically significant alpha for only two portfolios. Out of 25 portfolios, three have significant alphas in the FFAF, while four portfolios have them in the FF3, FFPS, HXZ, FF5, FF4, and SY4 models. In contrast, the FFC model generates 14 significant alphas, which is the highest number among all the factor pricing models. Moreover, all but the CAPM and the FFC model have a statistically significant alpha for one out of five portfolios in the smallest size quintile. In summary, all of my results suggest that, despite rejection on the Gibbons, Ross, and Shanken (1989) test, the FF3, FFPS, and FF4 models are the three best factor pricing models accommodating the average excess returns on size and CI sorted portfolios.

### 1.3.3 Size-DR (distress risk) portfolios

The results for the 25 size-DR portfolios in Panel C indicate that all but the CAPM and the HXZ model are rejected by the Gibbons, Ross, and Shanken (1989) test at the 5% level of significance. The CAPM generates the smallest GRS statistic of 0.953 ($p$-value = 0.530). The model also generates the largest value, 0.973, for the ratio $As^2(\alpha_i)/A\alpha_i^2$. But the HXZ model shows the best performance by producing the smallest value of 0.082% per

month for $A|\alpha_i|$, the smallest values of 0.452 and 0.257, respectively, for the alpha dispersion metrics $A|\alpha_i|/A|\overline{r}_i|$ and $A\alpha_i^2/A\overline{r}_i^2$, and the smallest value of 0.484 for $Sh^2(\alpha)$. The model also generates the second smallest GRS statistic of 1.518. The BS6 model, which is the best model in explaining size and STR sorted portfolios, now shows a superior performance only in terms of producing the largest point estimate for $A(R^2)$. Both the FF5 and the SY4 models show reasonably good performance when judged by their $A|\alpha_i|$, $A|\alpha_i|/A|\overline{r}_i|$, $A\alpha_i^2/A\overline{r}_i^2$, and $A(R^2)$ estimates. Coincidentally, the point estimates of $Sh^2(\alpha)$ produced by the FF5 and FF4 models are the same, 0.493.

My results in Table 1.A4 of the Appendix show that only the CAPM and the HXZ model generate statistically insignificant alphas across the 25 size-DR portfolios. Among the remaining factor pricing models being compared, most of them have problems explaining average returns on the highest distress quintile portfolios. The exceptions are the FFC and SY4 models. I also see that the FFPS model performs the worst in terms of generating the least number of significant alphas for portfolios. In particular, the model produces eight alphas that are statistically distinguishable from zero. Taken together, all of the above results suggest that the HXZ model provides the best description of average size-DR portfolio excess returns.

### 1.3.4 Size-$\beta$ (market beta) portfolios

I observe in Table 1.1 that the rejections of the factor pricing models by the Gibbons, Ross, and Shanken (1989) test are weakest for the 25 size-$\beta$ portfolios. In fact, the null hypothesis of zero alphas cannot be rejected for the FFC and SY4 models at conventional levels of significance (Panel D). The SY4 model generates a smaller GRS statistic than the FFC model. The average absolute value of alphas is 0.063% per month for the SY4 model, which is smaller than those of other asset pricing models. The SY4 model also produces the smallest values of 0.319, 0.103, and 0.424 for pricing performance metrics $A|\alpha_i|/A|\overline{r}_i|$, $A\alpha_i^2/A\overline{r}_i^2$, and $Sh^2(\alpha)$, respectively. When judged by the point estimates of the GRS statistic, $A|\alpha_i|$, $A|\alpha_i|/A|\overline{r}_i|$, $A\alpha_i^2/A\overline{r}_i^2$, and $A(R^2)$, the CAPM turns out to be the worst performer among all the factor models.

Looking at the alphas, reported in the Appendix Table 1.A5, I find that the SY4 model outperforms all other factor pricing models. All alphas for the 25 size-$\beta$ portfolios relative to the model are statistically indistinguishable from zero. Although the FFC model comfortably passes the Gibbons, Ross, and Shanken (1989) test, the model generates three portfolio

alphas that are statistically significant. Notably, 13 out of 25 portfolios have a significant alpha relative to the FFAF model. In contrast, the HXZ, FF5, and FF4 models generate only two significant alphas each. To summarize, my results indicate that the SY4 model is the best performer in capturing the average excess returns on the 25 size-$\beta$ portfolios.

### 1.3.5 Size-NI (net share issues) portfolios

The Gibbons, Ross, and Shanken (1989) test on the 35 size-NI portfolios, shown in Panel E of Table 1.1, rejects all the asset pricing models at conventional levels of significance. Said differently, all of the models are incomplete descriptions of average excess returns on these anomaly portfolios. But the SY4 model produces the smallest GRS statistic of 2.780 ($p$-value = 0.000), followed by 3.133 ($p$-value = 0.000) for the HXZ model. Despite rejections, both these models appear to perform well based on a majority of metrics. The average absolute alphas from the two models are 0.109% and 0.104% per month. The FF5 and FF4 models also produce small values of $A|\alpha_i|$, both 0.110% per month. The dispersion of the alpha estimates for the HXZ model is about 43% as large as the dispersion of average excess returns on size-NI portfolios, whereas it is about 45% for the FF5, FF4, and SY4 models. The HXZ model has an edge over the SY4 model when judged by its $A\alpha_i^2/A\bar{r}_i^2$ ratio of 0.223. The corresponding point estimate is 0.251 for the SY4 model. Both the HXZ and the SY4 models show superior performance to the FF5, FF4, and other factor models, by producing larger values, of 0.503 and 0.496, for the ratio $As^2(\alpha_i)/A\alpha_i^2$. But the values of $A(R^2)$ for the FF5 and FF4 models are marginally higher than those for the HXZ and SY4 models. When it comes to $Sh^2(\alpha)$, the SY4 model outperforms all the competing asset pricing models by generating the smallest value of 1.180 for the metric. The HXZ model lines up as the next best performer, with a value of 1.268.

The results reported in the Appendix Table 1.A6 show that the SY4 model outperforms other candidate factor models by producing only three significant alphas. Moreover, only one out of these three significant alphas is located in the smallest size quintile. The HXZ model is the next best performer, as it generates five alphas that are statistically distinguishable from zero. Conversely, both in the CAPM and the FFAF model, 15 out of 35 anomaly portfolios have statistically significant alphas. All these results show that the SY4 and HXZ models are the top two performers in the tests on the 35 size-NI portfolios, though the former model has a marginal edge over the latter when judged by the number of significant alphas.

### 1.3.6 Size-MAX (lottery demand) portfolios

In Panel F of Table 1.1, I see that the Gibbons, Ross, and Shanken (1989) test on the 25 size-MAX portfolios strongly rejects all of the competing models. Although rejected by the test, the SY4 model stands out as the best, based on a majority of the performance metrics. For example, the average absolute alpha relative to the model is 0.141% per month, which is smaller than that for any other factor pricing model. The SY4 model also produces the smallest value, of 0.507, and the second smallest value, of 0.275, respectively, for the ratios $A|\alpha_i|/A|\overline{r}_i|$ and $A\alpha_i^2/A\overline{r}_i^2$. About 27% of the dispersion (second moment) of the alpha estimates for the model can be attributed to sampling error. Judged by the same $As^2(\alpha_i)/A\alpha_i^2$ ratio, the BS6 model turns out to be the next best model, with a value of 0.235. On that metric, $As^2(\alpha_i)/A\alpha_i^2$, the FFAF model emerges as the worst-performing asset pricing model, with a value of 0.060. I see that the FF5 and BS6 models deliver high and nearly identical values of $A(R^2)$. When examining the value of $Sh^2(\alpha)$, it can be observed that the HXZ model generates the smallest value of 0.867. The corresponding value for the SY4 model is slightly higher at 0.888.

Examining the portfolio alphas, reported in the Appendix Table 1.A7, I find that all of the models have difficulty explaining average excess returns on microcap portfolios. The HXZ model produces a statistically significant alpha for four portfolios and two of them are located in the microcap quintile. Out of 25 portfolios, six have significant alphas in the SY4 model, while eight portfolios have them in the FF5, FF4, and BS6 models. The FFAF model is ranked at the bottom. The model produces a statistically significant alpha for 15 portfolios. Overall, these results suggest that the SY4 model has a superior ability to accommodate, though not completely, the average excess returns on the 25 size-MAX portfolios.

### 1.3.7 Size-RVar (residual variance) portfolios

The results in Panel G of Table 1.1, for the 25 size-RVar portfolios, show that the Gibbons, Ross, and Shanken (1989) test strongly rejects all the asset pricing models. Notably, I find that the GRS statistics for models are large in general – an observation similar to that reported in Fama and French (2016). The SY4 model generates the smallest average absolute alpha, of 0.116% per month, and the smallest point estimate, of 0.373, for the ratio $A|\alpha_i|/A|\overline{r}_i|$. Conversely, the HXZ model produces the smallest value, of 0.213, for the ratio $A\alpha_i^2/A\overline{r}_i^2$ and the largest value, of 0.273, for the ratio $As^2(\alpha_i)/A\alpha_i^2$. I also notice that the

FF5 model ranks first among the factor pricing models when judged by the point estimate of $A(R^2)$.

The anomaly portfolio alphas, reported in the Appendix Table 1.A8, show that the HXZ model produces a statistically significant alpha for four portfolios and only two of them are located in the smallest size quintile. The SY4 model also produces four significant alphas, but three of them are located in the smallest size quintile. I see an improvement for the FF4 model over its performance in the 25 size-MAX portfolios. Specifically, the model now produces four significant alphas and only one of them is located in the microcap quintile. The FF5 and BS6 models also show similar improvements in performance based on this criterion. The CAPM, however, ranks last among the factor pricing models. Out of 25 portfolios, 17 have significant alphas relative to the model. It is worth noting that across the ten sets of anomaly portfolios, this is the highest number of statistically significant alphas generated by any model. In summary, both the HXZ and the SY4 models are the two best, but still imperfect, models explaining the average excess returns on the 25 size-RVar portfolios.

### 1.3.8 Size-AC (accruals) portfolios

I find in Panel H of Table 1.1 that the Gibbons, Ross, and Shanken (1989) test easily rejects all the models considered for the 25 size-AC portfolios. Although the competing models are incomplete descriptions of average excess returns on these portfolios, the SY4 model delivers the best performance on more than half of the metrics. For example, it produces the smallest GRS statistic, of 2.818, the smallest average absolute alpha, of 0.095% per month, and the smallest point estimate, of 0.530, for the alpha dispersion metric $A|\alpha_i|/A|\bar{r}_i|$. Among the other factor models, there is a noteworthy improvement in performance for the CAPM when I consider $As^2(\alpha_i)/A\alpha_i^2$, which is 0.485. The corresponding point estimate of the metric is 0.495 for the SY4 model, which is the largest value across all the asset pricing models tested on AC anomaly portfolios. I also find that the CAPM delivers the smallest value, of 0.725, for $Sh^2(\alpha)$.

Out of 25 accruals anomaly portfolios, reported in the Appendix Table 1.A9, only three have statistically significant alphas relative to the SY4 model. The CAPM produces four significant alphas and none of them are located in the smallest size quintile. The performance of the FF3, FF5, and FF4 models do not bode well since each of these models produces ten alphas that are statistically distinguishable from zero. This finding is in line with the evidence provided by Fama and French (2016). I also notice that for a majority of the asset pricing

models, the main problem is to explain the average excess returns of the biggest size stocks and the stocks in the highest AC quintile.

### 1.3.9 IND (industry) portfolios

Turning now to the 30 IND portfolios, the results for which are shown in Panel I of Table 1.1, I find that the Gibbons, Ross, and Shanken (1989) test rejects almost all of the factor models at conventional significance levels. The sole exception is the CAPM, which produces a GRS statistic of 1.311 ($p$-value = 0.127). Moreover, informally comparing the competing models based on the point estimates of performance metrics reveals that the CAPM is the top contender in the horse race. Overall, the SY4 model takes second place, while the BS6 model ranks last among the candidate factor models. Specifically, the average absolute alpha is 0.150% per month for the CAPM, which is lower than the value of 0.180% per month for the SY4 model. Likewise, the point estimates of the ratios $A|\alpha_i|/A|\overline{r}_i|$ and $A\alpha_i^2/A\overline{r}_i^2$ are, respectively, 1.173 and 1.630 for the CAPM, which are much smaller than those of 1.401 and 1.774 for the SY4 model. But on the basis of $A(R^2)$ and the ratio $As^2(\alpha_i)/A\alpha_i^2$, the SY4 model shows a marginal edge over the CAPM. Notably, the CAPM performs marginally better than the SY4 model when judged on the point estimate of $Sh^2(\alpha)$. On the same criterion, the FF5 model performs the best, as it generates the smallest point estimate of 0.622. The model also produces the largest value for $A(R^2)$, which is consistent with Stambaugh and Yuan (2016), who informally compare factor models, such as the CAPM, FF3, HXZ, FF5, and SY4 models, using the 30 IND portfolios.

Table 1.A10 in the Appendix shows that the CAPM and the SY4 model are the top performers. Both these models produce alphas for four portfolios that are statistically distinguishable from zero. In contrast, the BS6 model produces as many as 11 significant alphas. The number of significant alphas is ten relative to both the FF5 and the FF4 models, while seven relative to the FFC, FFAF, and HXZ models. The superior performance of the CAPM in producing the least number of significant alphas for industry portfolios is also consistent with the evidence by Fama and French (1997), who compare the model with the FF3 model.

### 1.3.10 D10−1 (high minus low decile) portfolios

I next consider the set of D10−1 portfolios corresponding to eight anomalies (i.e., STR, CI, DR, market $\beta$, NI, MAX, RVar, and AC) and examine the abilities of the competing asset pricing models to explain the average excess returns on these long-short portfolios. Panel J in Table 1.1 shows that all the models are strongly rejected by the Gibbons, Ross,

and Shanken (1989) test. An informal analysis of the performance metrics suggests that the SY4 model is the best, though still incomplete, description of average excess returns on these anomaly portfolios. The average absolute alpha for portfolios is 0.259% per month in the model, which is the smallest value for the metric across all models. The $A|\alpha_i|/A|\overline{r}_i|$ ratio of 0.307 for the SY4 model is small compared with those of competing factor models. The HXZ model also does a good job in explaining the set of anomaly long-short spreads. The model generates a value of 0.262% per month for $A|\alpha_i|$, which is marginally higher than that for the SY4 model. About 31% of the dispersion (second moment) of the alpha estimates for the model is due to sampling error. All other asset pricing models fare poorly on this dispersion metric. I also find that the BS6 model generates the largest point estimate for $A(R^2)$, while the FF5 model produces the smallest point estimate for $Sh^2(\alpha)$. Overall, the FFAF model performs the worst in the horse race among all models.

The results in the Appendix Table 1.A11 suggest that both the HXZ and the SY4 models are superior to other competing models, as each of these models generates only two significant alphas. Specifically, the HXZ model generates a statistically significant alpha for the D10−1 portfolios corresponding to NI and AC anomalies, while the SY4 model generates a significant alpha for the D10−1 portfolios sorted on STR and AC. The BS6 model also performs well in explaining average returns on anomaly portfolios. The model generates significant alphas for the high-minus-low portfolios that are sorted on DR, NI, and AC. Consistent with the findings in Table 1.1 (Panel J), the FFAF model ranks last. Out of eight anomaly long-short portfolios, seven have significant alphas relative to the model. Finally, none of the asset pricing models accommodates average return on the D10−1 portfolio corresponding to AC anomaly.

### 1.3.11 Overall model performance in time-series regressions

To facilitate discussion in this section, Table 1.2 summarizes the overall performance of each of the return factor models in the time-series regressions presented in Table 1.1 and Tables 1.A2 through 1.A12 of the Appendix. Columns 1 to 7 report the number of the sets of anomaly portfolios across which a given asset pricing model performs the best. More precisely, the criteria for overall performance evaluation are the number of times a competing model generates the smallest point estimates of the GRS statistic, $A|\alpha_i|$, $A|\alpha_i|/A|\overline{r}_i|$, $A\alpha_i^2/A\overline{r}_i^2$, and $Sh^2(\alpha)$, and the largest point estimates of $As^2(\alpha_i)/A\alpha_i^2$ and $A(R^2)$ metrics. In columns 8 to 17, I provide the number of statistically significant alphas relative to a given factor model tested on each set of anomaly portfolios. The last column of Table 1.2 shows,

for each asset pricing model, the number of significant alphas out of 42 small size portfolios from the eight anomaly variables, STR, CI, DR, market $\beta$, NI, MAX, RVar, and AC.

Starting with the Gibbons, Ross, and Shanken (1989) test, I see that the SY4 model outperforms all the competing models by producing the smallest GRS statistic in five out of the ten sets of portfolios. The CAPM ranks second in my list of models, as it generates the smallest GRS statistic in two sets of portfolios. The results also show that the HXZ, FF4, and BS6 models each produce the smallest GRS statistic in one set of portfolios. For the metric $A|\alpha_i|$, which measures the unexplained average absolute excess return, the SY4 model generates the smallest point estimate in five out of the ten sets of portfolios and the HXZ model delivers the smallest value in two sets of portfolios. The SY4 model continues to outperform its nine competing models by generating the smallest value for the ratio $A|\alpha_i|/A|\overline{r}_i|$ and the largest value for the ratio $As^2(\alpha_i)/A\alpha_i^2$, respectively, in five and four sets of test asset portfolios. In contrast, the number of times the HXZ model generates the smallest $A|\alpha_i|/A|\overline{r}_i|$ ratio and the largest $As^2(\alpha_i)/A\alpha_i^2$ ratio are, respectively, two and three. The HXZ model ranks first among the models when assessed by the point estimate of the alpha dispersion metric, $A\alpha_i^2/A\overline{r}_i^2$. The model generates the smallest point estimate in four out of the ten sets of portfolios. When assessed by the point estimate of $A(R^2)$, I find that the FF5 and BS6 models do a better job than the other models in explaining average excess returns. Both these models deliver the largest value for the metric in five out of the ten sets of portfolios. For the $Sh^2(\alpha)$ criterion, the HXZ, FF5, FF4, and SY4 models turn out to be the best performers, as each of these models generates the smallest point estimate for the metric in two sets of test asset portfolios.

Comparing the number of statistically significant alphas generated by each of the factor models, I find the SY4 model is the best performer. The model delivers the least number of significant alphas for the 25 size-$\beta$ portfolios, the 35 size-NI portfolios, the 25 size-RVar portfolios, the 25 size-AC portfolios, the 30 IND portfolios, and the 8 D10$-$1 portfolios. The HXZ, BS6, FF4, and FF5 models take second, third, fourth, and fifth places, respectively. The SY4 model also turns out to be one of the top performers in explaining the average excess returns on portfolios with small stocks. Out of 42 small size portfolios, the number of significant alphas is 11 in the SY4 model, 10 in the BS6 model, and 12 in the HXZ, FF5, and FF4 models. In contrast, both the FFC model and the FFAF model generate statistically significant alphas for 19 portfolios, which is the highest number of significant alphas for small size portfolios produced by any model. The corresponding number for the CAPM is 15, while for the FF3 and FFPS models it is 16. This clearly suggests that all of

the asset pricing models have some difficulty in explaining returns on small stocks. Overall, the time-series results in Tables 1.1 and 1.2 indicate that the SY4 model is the best model, in that it outperforms other models on most performance metrics. The HXZ model takes second place, while the FF5 and BS6 models, performing about equally well, take joint third place. Stambaugh and Yuan (2016) also report a similar ranking when comparing only the FF3, HXZ, FF5, and SY4 models, although their test assets in time-series regressions are different from those employed in this chapter.

Common to many recent papers (see, for example, Fama and French, 2015, 2016; Hou, Xue, and Zhang, 2015, 2017a), the above time-series analyses of the relative performance of factor models can be criticized on the grounds that they are conducted without any use of a formal statistical criterion. The ranking of models might differ when their relative performance is tested statistically. In the following section, I investigate whether a competing asset pricing model is significantly better than another candidate model by employing the pairwise test for equality of cross-sectional regression $R^2$s. The pairwise test accounts for the impact of potential model misspecification and therefore enables us to draw valid statistical inferences on the relative performance of the competing models. Finally, I conduct the multiple model comparison analyses to identify whether a given asset pricing model significantly outperforms a set of alternative models in terms of the OLS (GLS) cross-sectional regression $R^2$.

## 1.4 Cross-sectional results[11]

### 1.4.1 Size-STR (short-term reversal) portfolios

Table 1.3 reports pairwise tests of equality of cross-sectional regression $R^2$s for the ten return factor models, estimated using the value-weighted monthly excess returns on the 25 size-STR portfolios. Some of the models are nonnested and in those cases I present results of the normal test described in Section 1.2.4.1. The results based on the OLS cross-sectional regressions in Panel A show that the CAPM is outperformed by some of the asset pricing models. That is, the CAPM generates a significantly lower cross-sectional $R^2$ than the FF3, FFAF, FF4, and BS6 models. This is not the case for the HXZ, FF5, and SY4 models, although the OLS $R^2$ differences with the CAPM still exceed more than 50 percentage points. This result also shows that the common practice of simply comparing the point estimate of a given performance metric can be misleading for identifying a superior asset pricing model.

[11] Throughout this section, I reject $\boldsymbol{H_0}$: $\boldsymbol{\rho_A^2 = \rho_B^2}$ if the corresponding $\boldsymbol{p}$-value is at most 0.05.

The BS6 model, which is the best model in the time-series regressions for this set of test asset portfolios, now significantly dominates only the CAPM. I find that the FF5, FF4, SY4, and BS6 models generate higher OLS cross-sectional regression $R^2$s than the HXZ model, but the differences are not statistically distinguishable from zero. Likewise, the FF5 model generates a higher cross-sectional $R^2$ than the FF4 and SY4 models, but the differences are not significant even at the 10% level.

In Panel B, which reports equality of $R^2$s test results based on the GLS cross-sectional regressions, I find that the FF3, FFC, FFPS, FFAF, FF4, and BS6 models outperform the CAPM. The relative performance of other factor pricing models is similar to that observed for the OLS cross-sectional regressions shown in Panel A. To summarize, the pairwise cross-sectional regression $R^2$ equality test results in Panels A and B favor the FF3, FFAF, FF4, and BS6 models over the remaining asset pricing models when judged by the number of times they significantly dominate another model. But focusing only on the SY4, HXZ, FF5, and BS6 models, which are the top four performing models in the time-series regressions, I find none of them is significantly better than the other three in pairwise tests. Thus, from this point of view, the performances of these four recently proposed asset pricing models are not different from each other when tested on the 25 size-STR portfolios.

Panel A of Table 1.14 reports multiple model comparison tests of the OLS and GLS cross-sectional $R^2$s for all the factor models, where I differentiate between the nested and the nonnested models. The results based on both the OLS and the GLS cross-sectional regressions, which take into account the process of searching over alternative models, suggest that none of the asset pricing models is significantly dominated by the others at the 5% level. Notably, I cannot reject the CAPM, which is nested by the remaining nine factor models that I consider, although some of these models generate a cross-sectional $R^2$ that is three to four times higher.[12]

### 1.4.2 Size-CI (abnormal capital investment) portfolios

When using the value-weighted monthly excess returns on the 25 size-CI portfolios as test assets, it can be seen in Panel A of Table 1.4 that all but the FFC, SY4, and BS6 models have significantly higher $R^2$s than the CAPM. In fact, the OLS cross-sectional regression $R^2$ differences between these models and the CAPM exceed as much as 40 percentage points (see, for example, the HXZ model). I observe that there are several occasions on which

[12] Kan, Robotti, and Shanken (2013) provide similar evidence for the CAPM when tested on the 25 size-B/M portfolios and five industry portfolios.

a large $R^2$ difference does not lead to the rejection of the null hypothesis of equal $R^2$s for two competing factor pricing models. For example, the OLS cross-sectional $R^2$ of the BS6 model is higher than that of the FF5 model by about 13 percentage points, but still the null hypothesis cannot be rejected ($p$-value = 0.140). A qualitatively similar finding emerges in Panel B, where the GLS cross-sectional regression $R^2$ of the BS6 model is higher than that of the FF5 model by about 18 percentage points, and still the difference in $R^2$ is statistically insignificant at conventional levels. I also find that the CAPM produces a cross-sectional $R^2$ that is statistically lower than those of any of the competing models estimated by the GLS regressions. Furthermore, in Panel B, both the FFC and the SY4 models now show an improved performance. For example, the SY4 model significantly outperforms the FFAF model. It is worth emphasizing that the HXZ, FF5, SY4, and BS6 models are never statistically dominated at the 5% level in Panels A and B. Overall, my pairwise test results based on the OLS and GLS cross-sectional regression $R^2$s indicate that the FFC model performs the best in explaining the average excess returns on the 25 size-CI portfolios. The FF3, FFPS, and FF4 models, which are the three best factor models identified informally for this set of test asset portfolios in the time-series regressions, no longer perform well in the horse race. Examining the multiple model comparison test results, reported in Panel B of Table 1.14, I find that the FFAF (GLS) model is rejected at the 5% significance level. Despite the lower cross-sectional regression $R^2$ of the CAPM, I fail to reject the null hypothesis that it performs at least as well as all other asset pricing models.

### 1.4.3 Size-DR (distress risk) portfolios

In Table 1.5, I report the results on factor pricing model performance in the 25 size-DR portfolios. The pairwise tests of equality of the OLS cross-sectional regression $R^2$s in Panel A reveal that none of the models either statistically outperforms or is outperformed by any of the other models at conventional significance levels. Hence, the 25 size-DR portfolios present the biggest challenge for all the asset pricing models. A similar picture emerges when model performance is analyzed on the basis of differences in the GLS cross-sectional regression $R^2$s (Panel B). There the $R^2$ differences exceed by as much as 26 percentage points but are still statistically insignificant. These findings from pairwise tests are consistent with those of the multiple model comparison tests in Panel C of Table 1.14. All of the $p$-values are above the conventional levels of significance, which suggests that none of the factor pricing models is outperformed by the rest of the models. Clearly, the above observation contrasts with that from the time-series regressions (see Panel C of Table 1.1), where the HXZ model is the best

performer in the horse race, though informally.

### 1.4.4 Size-$\beta$ (market beta) portfolios

Table 1.6 presents the results when the test assets are the 25 size-$\beta$ portfolios. In Panel A, I notice that only the HXZ, FF5, FF4, and SY4 models offer a somewhat superior performance by generating significantly higher OLS cross-sectional $R^2$s. Specifically, each of these factor pricing models outperforms the CAPM. Their $R^2$ differences with the CAPM exceed more than 70 percentage points. I emphasize that the relatively good performance of the SY4 model in Panel A is consistent with that observed for the time-series regressions using the same set of anomaly portfolios. The superior performance of the HXZ, FF5, FF4, and SY4 models can also be seen in Panel B, where pairwise tests of equality for $R^2$s are based on the GLS cross-sectional regressions. Consistent with Panel A, the CAPM again shows up as the worst-performing asset pricing model. This time it is additionally significantly outperformed by the FF3, FFC, and FFPS models. Overall, the OLS and GLS cross-sectional results show that the HXZ, FF5, FF4, and SY4 models do a relatively better job in explaining the average excess returns on size and market $\beta$ sorted portfolios. But looking at the multiple model comparison tests in Panel D of Table 1.14, I find that only the FFAF (GLS) model is rejected at the 5% level. Once again, the CAPM is not rejected at conventional levels of significance. That is, it performs at least as well as all others when assessed within the multiple model comparison framework.

### 1.4.5 Size-NI (net share issues) portfolios

The pairwise tests of equality for factor model $R^2$s based on the 35 size-NI portfolios in Table 1.7 show that the SY4 model is the best overall performer, followed by the HXZ model. In Panel A, showing results based on the OLS cross-sectional regression $R^2$s, it is observable that the SY4 model significantly dominates the CAPM, FF3, FFPS, and FFAF models. The HXZ model, however, fails to perform significantly better than the FFPS model in terms of $R^2$. The BS6 model now demonstrates an improved relative performance for this set of anomaly portfolios compared with those observed in Tables 1.3 through 1.6. The model outperforms the CAPM, FF3, and FFAF models by generating significantly higher OLS cross-sectional regression $R^2$s. However, in the pairwise test comparing the BS6 and FFPS models, I observe that the BS6 model is statistically outperformed by the FFPS model. I further notice that all but the FFC model easily outperform the CAPM. But the FFC model clearly dominates both the FF3 and the FFAF models. The results based on the GLS

cross-sectional regression $R^2$s show a better performance for the HXZ model compared with that observed in Panel A. Now, the HXZ model lines up as the best-performing asset pricing model, along with the SY4 model. However, the relative performances of the FF5, FF4, and BS6 models now fall short slightly. Specifically, these models are no longer able to generate a significantly higher GLS cross-sectional $R^2$ than the FF3 model. In Panels A and B, it can also be seen that the HXZ, FF5, and SY4 models are not outperformed in any of my pairwise $R^2$ tests. Furthermore, the relative performance of the SY4 model is consistent with that observed in the time-series regressions.

Turning now to the multiple model comparison test results, reported in Panel E of Table 1.14, I see that the CAPM (OLS) is rejected at the 5% level of significance. Moreover, for the OLS-based comparisons, the FF3 and FFAF models are statistically dominated. The GLS-based comparison tests show that the FF3, FFPS, and FFAF models are dominated at the 5% level. Notably, the CAPM (GLS) marginally misses rejection of the null hypothesis with a $p$-value of 0.051. As for the remaining asset pricing models, the corresponding $p$-values suggest that none of them can be rejected in the multiple model comparison tests of the OLS and GLS $R^2$s.

### 1.4.6 Size-MAX (lottery demand) portfolios

Moving to the 25 size-MAX portfolios, in Table 1.8, I find that the CAPM is outperformed by most other asset pricing models. In particular, the model shows a poor performance relative to all but the FF5 model in Panel A, for the OLS cross-sectional regressions. I also observe that in Panel A, the BS6 model demonstrates a somewhat better performance in explaining the average excess returns on portfolios. In addition to outperforming the CAPM, the model produces a significantly higher cross-sectional $R^2$ than the FFAF model. Looking at the pairwise test results in Panel B, based on the GLS cross-sectional regressions, I find that the relative performance of the CAPM improves marginally. Now it has no significant differences with those of the FFAF and BS6 models, in addition to the FF5 model, in terms of $R^2$. An improvement in performance of the HXZ, FF5, FF4, and SY4 models can also be observed, as these models now generate statistically higher GLS cross-sectional regression $R^2$s than the FFAF model. Taken together, the pairwise test results in Panels A and B indicate that the HXZ, FF4, SY4, and BS6 models are the top performers among the ten factor pricing models being compared. Finally, focusing on the OLS- and GLS-based multiple model comparison test results in Panel F of Table 1.14, I find that only the FFAF (GLS) model is rejected at the 5% level of significance.

### 1.4.7 Size-RVar (residual variance) portfolios

The CAPM turns out to be the worst when I conduct the pairwise cross-sectional regression $R^2$ equality tests for the asset pricing models using monthly excess returns on the 25 size-RVar portfolios, as shown in Table 1.9. On the other hand, both the FF5 and the FF4 models consistently exhibit the best overall performance, although neither is statistically better than the HXZ or BS6 model in terms of the cross-sectional $R^2$. The most striking result in Table 1.9 is that both the FF5 and FF4 models now statistically dominate the SY4 model (see Panel B). The GLS cross-sectional regression $R^2$ differences with the SY4 model exceed more than 25 percentage points. In Panel A, it is also observable that the HXZ and BS6 models are jointly ranked, after the FF5 and FF4 models, in terms of the number of times they dominate another asset pricing model. Between these two models, however, the BS6 model is statistically dominated by the FFPS model in the pairwise test of equality of cross-sectional $R^2$s. The relative performance of the BS6 model improves markedly in Panel B, where it is no longer dominated by the FFPS model. In fact, I see the opposite: the FFPS model is now statistically outperformed by the BS6 model. On the other hand, the performance of the HXZ model drops slightly, as it fails to generate a statistically higher GLS cross-sectional $R^2$ than the FF3 model. In Panel B, I further notice that the SY4 model's performance is at a minimum in terms of statistically outperforming other factor pricing models, in that it is significantly better than only one other model, namely the CAPM. Finally, for the OLS-based multiple model comparisons in Panel G of Table 1.14, it can be seen that the FF3, FFPS, and FFAF models are rejected at the 5% level. The number of model rejections increases when I consider the GLS-based multiple model comparison tests. Now, the FFC and SY4 models are also dominated at the 5% level of significance. All these results on the performance of the factor pricing models contrast with those in the time-series regressions for the 25 size-RVar portfolios.

### 1.4.8 Size-AC (accruals) portfolios

The $R^2$ equality tests using the 25 size-AC portfolios in Table 1.10 show a best overall performance for the FF4 model. The FFC and FF5 models also show a modest performance in the horse race, as they generate significantly higher OLS cross-sectional regression $R^2$s than the FF3 model and the CAPM, respectively. Among the remaining competing asset pricing models, it can be seen that none either statistically dominates or is dominated by any of the other models at the 5% level. I notice that both the FFC and the FF5 models fail to outperform any of the other models in Panel B, showing the GLS cross-sectional regressions.

Consistent with the findings in Panel A, I see that the HXZ, FF5, SY4, and BS6 models neither statistically dominate nor are dominated by any of the competing factor models. This evidence contrasts with the good performance of the SY4 model in the time-series regressions using the same set of anomaly portfolios. Further, analyzing the multiple model comparison test results in Panel H of Table 1.14, I find that only the FF3 (OLS) model is statistically dominated by the others.

### 1.4.9 IND (industry) portfolios

I see in Panel A of Table 1.11 that none of the asset pricing models either statistically outperforms or is outperformed by any of the other competing models. All of the $p$-values are much higher than the 10% level of significance. The statistical inferences about model performance also remain the same when I look at the pairwise tests of equality for the GLS cross-sectional regression $R^2$s in Panel B. Clearly, these observations suggest that the 30 IND portfolios pose a serious challenge for all of the factor pricing models. When model performance is analyzed, in Panel I of Table 1.14, using the multiple model comparison tests, I once again see that none of the models is rejected at conventional significance levels. This empirical evidence contrasts with that from the time-series regressions, in Panel I of Table 1.1, where an informal comparison of performance metrics suggests the CAPM is the best model.

### 1.4.10 D10−1 (high minus low decile) portfolios

Table 1.12 reports the results based on the set of D10−1 portfolios corresponding to eight anomalies. The pairwise tests of equality for the OLS cross-sectional regression $R^2$s in Panel A show that most of the models significantly outperform the CAPM. The two exceptions are the FFPS and FFAF models. Although both these models generate a higher cross-sectional $R^2$ than the CAPM, the differences are statistically indistinguishable from zero (at the 5% level). A somewhat similar picture emerges in Panel B, with the GLS cross-sectional regressions, where I see that only the FFPS model fails to outperform the CAPM. I further find, in Panels A and B, that the FF3, FFC, FFPS, FFAF, HXZ, FF5, FF4, SY4, and BS6 models are never statistically dominated in any of my pairwise tests of equality for cross-sectional regression $R^2$s. These results on the relative performance of the factor pricing models contrast with those in the time-series regressions for the same set of anomaly long-short portfolios. Finally, in Panel J of Table 1.14, I see that the FFAF model is statistically dominated at the conventional 5% level when the GLS-based multiple model

comparison tests are considered.[13]

### 1.4.11 Overall model performance in cross-sectional regressions

I summarize the pairwise cross-sectional regression $R^2$ equality test results from Tables 1.3 through 1.12 for all the asset pricing models in Table 1.13. In Panel A, for the OLS-based results, it can be seen that the FF4 model offers the best overall performance, in that it statistically outperforms competing asset pricing models the most times in a majority of the sets of test asset portfolios. The FF5 model takes second place in the horse race. The HXZ and BS6 models, which perform about equally well, turn out jointly to be the next best models. It also appears that the SY4 model fails to secure a position in the top three places among the ten different return factor models. Analyzing the GLS cross-sectional regression based test results in Panel B, I once again find that the FF4 and FF5 models secure the first and the second places, respectively. But the SY4 model now takes joint third place, along with the HXZ and BS6 models. I emphasize that in Panels A and B, the HXZ, FF5, and FF4 models are the only asset pricing models that are never statistically outperformed at the 5% level in any of my pairwise $R^2$ tests. The results from the sequential tests for nonnested models reported in the Appendix also corroborate my findings in Table 1.13.

But looking at the multiple model comparison test results, summarized in Table 1.15, I see that only the HXZ, FF5, FF4, and BS6 models are never rejected at the 5% level of significance. I highlight that this observation holds regardless of whether the OLS- or GLS-based multiple model comparison tests are employed. I also find that the SY4 model is rejected in one out the ten sets of test asset portfolios. Although these findings are slightly different from those summarized in Table 1.13, they can be rationalized by the fact that the pairwise model comparisons do not take into account the process of searching across alternative factor pricing models. Consequently, the pairwise testing procedure can lead to an overstatement of statistical significance (see Barillas, Kan, Robotti, and Shanken, 2017; Kan, Robotti, and Shanken, 2013).

Taken together, my cross-sectional empirical results summarized in Tables 1.13 and 1.15 suggest that the HXZ, FF5, FF4, and BS6 models perform about equally well and jointly take first place in the horse race. The SY4 model, which is the top performer in the time-series regressions, is now the next best asset pricing model. Importantly, I also notice that the

[13] I do not report results for the CAPM in Panel J of Table 1.14, as there are more factors in the expanded model than the cross-sectional data points. In this case, no unique solution exists for the second-pass regression.

CAPM performs reasonably good – evidence that is different from most empirical studies based on time-series regressions (see, among others, Fama and French, 1996, 2016; Hou, Xue, and Zhang, 2015, 2017a; Stambaugh and Yuan, 2016). These cross-sectional statistical findings on the relative performance of the return factor models are different from my informal findings in the time-series regressions, reported in Section 1.3. They can be rationalized by two possible reasons. First, in the time-series regression, a return factor receives a zero pricing error in each sample because the factor risk premium is estimated as the sample mean of the factor, whereas the cross-sectional regression minimizes the sum of squares of all the pricing errors (see Cochrane, 2005, p. 244). Second, in the cross-sectional approach, I compare the different factor pricing models by relying on formal statistical methods and therefore take into account the sampling variability. Moreover, the cross-sectional statistical tests allow for potential model misspecification, that is, population deviations from the model. I acknowledge that although model comparison can be sensitive to the test assets, the findings from the tests based on cross-sectional regressions are fairly robust across the various sets of test asset portfolios. my pairwise $R^2$ equality test and the multiple model comparison test results reinforce the argument of Barillas and Shanken (2017) and Harvey and Liu (2017) that factor model comparison conducted informally, by eyeballing point estimates of pricing performance metrics, can be misleading.

## 1.5 Conclusion

This chapter compares the performance of ten different asset pricing models in explaining the average excess returns on various sets of prominent anomaly portfolios. My list of models comprises the capital asset pricing model of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor model, the Asness and Frazzini (2013) three-factor model, the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, the Stambaugh and Yuan (2016) four-factor model, and the Barillas and Shanken (2018) six-factor model. An informal analysis based on a comprehensive set of performance metrics in the time-series domain shows that the Stambaugh and Yuan (2016) four-factor model provides the best, though still incomplete, description of average monthly excess returns on a majority of my test asset portfolios. The Hou, Xue, and Zhang (2015) $q$-factor model takes second place, while the Fama and French (2015) five-factor model and the Barillas and Shanken (2018) six-factor model jointly take

third place in the horse race.

However, a different picture emerges when the relative performance of all the models is tested statistically using the pairwise cross-sectional regression $R^2$ equality test and the multiple model comparison test. I find that the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, and the Barillas and Shanken (2018) six-factor model perform about equally well and take equal first place. The Stambaugh and Yuan (2016) four-factor model, which is the top performer in the time-series regressions, turns out to be the next best model. Unlike previous empirical studies, I also find that the capital asset pricing model of Sharpe (1964) and Lintner (1965) performs reasonably well. My cross-sectional findings remain robust irrespective of regression methodologies and sequential tests for nonnested models. All these results also indicate that the common practice of identifying the superior model(s) by informally comparing pricing performance metrics can sometimes be misleading. Taken together, my empirical findings have important implications for practitioners who need to evaluate capital budgeting, equity valuation, investment management, and fund performance.

Table 1.1: Performance of factor models in time-series (absolute) tests

The table reports summary statistics for time-series (absolute) tests of ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on anomaly portfolios: the 25 size-STR (short-term reversal) portfolios, the 25 size-CI (abnormal capital investment) portfolios, the 25 size-DR (distress risk) portfolios, the 25 size-$\beta$ (market beta) portfolios, the 35 size-NI (net share issues) portfolios, the 25 size-MAX (lottery demand) portfolios, the 25 size-RVar (residual variance) portfolios, the 25 size-AC (accruals) portfolios, the 30 IND (industry) portfolios, and the 8 D10−1 (high minus low decile) portfolios. For each of the factor models, GRS is the $F$-statistic of the Gibbons, Ross, and Shanken (1989) test on the null hypothesis that the alphas (i.e., intercepts in time-series regressions) across a given set of anomaly portfolios are jointly equal to zero, $p$(GRS) is the $p$-value associated with the GRS statistic (i.e., $F$-statistic), $A|\alpha_i|$ is the average absolute value of the alphas, $A|\alpha_i|/A|\overline{r}_i|$ is the ratio of the average absolute value of the alphas to the average absolute value of $\overline{r}_i$ estimated as the average excess return on an anomaly portfolio $i$ minus the value-weighted average excess return on the market portfolio, $A\alpha_i^2/A\overline{r}_i^2$ is the ratio of the average squared alpha to the average squared value of $\overline{r}_i$, $As^2(\alpha_i)/A\alpha_i^2$ is the ratio defined as the average variance estimate of the sampling errors of the estimated alphas to $A\alpha_i^2$, $A(R^2)$ is the average value of the time-series regression $R^2$ adjusted for degrees of freedom, $Sh^2(f)$ is the maximum squared Sharpe ratio of the factor(s), $Sh_B^2(f)$ is the average of $Sh^2(f)$ from 100,000 full-sample bootstrap simulation runs, and $Sh^2(\alpha)$ is the maximum squared Sharpe ratio for the alphas across a given set of anomaly portfolios. The sample period is from January 1968 to December 2016.

| Model | GRS | $p$(GRS) | $A\lvert\alpha_i\rvert$ | $\frac{A\lvert\alpha_i\rvert}{A\lvert\overline{r}_i\rvert}$ | $\frac{A\alpha_i^2}{A\overline{r}_i^2}$ | $\frac{As^2(\alpha_i)}{A\alpha_i^2}$ | $A(R^2)$ | $Sh^2(f)$ | $Sh_B^2(f)$ | $Sh^2(\alpha)$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | Panel A: 25 size-STR portfolios | | | | | | | | | |
| CAPM | 4.147 | 0.000 | 0.202 | 0.842 | 0.708 | 0.241 | 0.752 | 0.012 | 0.012 | 0.732 |
| FF3 | 4.373 | 0.000 | 0.155 | 0.647 | 0.558 | 0.164 | 0.866 | 0.043 | 0.032 | 0.709 |
| FFC | 4.403 | 0.000 | 0.191 | 0.793 | 0.750 | 0.119 | 0.875 | 0.086 | 0.054 | 0.803 |
| FFPS | 4.502 | 0.000 | 0.150 | 0.625 | 0.546 | 0.169 | 0.866 | 0.056 | 0.046 | 0.704 |
| FFAF | 4.444 | 0.000 | 0.144 | 0.599 | 0.532 | 0.162 | 0.872 | 0.027 | 0.026 | 0.746 |
| HXZ | 3.887 | 0.000 | 0.176 | 0.733 | 0.707 | 0.146 | 0.866 | 0.182 | 0.118 | 0.729 |
| FF5 | 4.041 | 0.000 | 0.160 | 0.668 | 0.550 | 0.165 | 0.874 | 0.107 | 0.078 | 0.749 |
| FF4 | 4.045 | 0.000 | 0.160 | 0.666 | 0.544 | 0.173 | 0.869 | 0.107 | 0.060 | 0.685 |
| SY4 | 4.902 | 0.000 | 0.230 | 0.956 | 1.097 | 0.096 | 0.870 | 0.233 | 0.112 | 0.877 |
| BS6 | 3.830 | 0.000 | 0.163 | 0.677 | 0.531 | 0.179 | 0.883 | 0.237 | 0.147 | 0.746 |
| | Panel B: 25 size-CI portfolios | | | | | | | | | |
| CAPM | 2.797 | 0.000 | 0.183 | 0.743 | 0.610 | 0.280 | 0.755 | 0.012 | 0.012 | 0.597 |
| FF3 | 2.196 | 0.001 | 0.081 | 0.329 | 0.121 | 0.660 | 0.885 | 0.043 | 0.032 | 0.587 |
| FFC | 3.011 | 0.000 | 0.156 | 0.635 | 0.381 | 0.197 | 0.895 | 0.086 | 0.054 | 0.899 |
| FFPS | 2.233 | 0.001 | 0.079 | 0.323 | 0.123 | 0.658 | 0.886 | 0.056 | 0.046 | 0.575 |
| FFAF | 2.463 | 0.000 | 0.091 | 0.371 | 0.148 | 0.483 | 0.894 | 0.027 | 0.026 | 0.645 |
| HXZ | 2.339 | 0.000 | 0.145 | 0.591 | 0.382 | 0.239 | 0.885 | 0.182 | 0.118 | 0.633 |
| FF5 | 1.997 | 0.003 | 0.082 | 0.335 | 0.145 | 0.547 | 0.893 | 0.107 | 0.078 | 0.559 |
| FF4 | 1.981 | 0.003 | 0.081 | 0.330 | 0.142 | 0.585 | 0.888 | 0.107 | 0.060 | 0.556 |
| SY4 | 1.987 | 0.003 | 0.119 | 0.485 | 0.247 | 0.394 | 0.881 | 0.233 | 0.112 | 0.631 |
| BS6 | 2.355 | 0.000 | 0.097 | 0.397 | 0.215 | 0.361 | 0.904 | 0.237 | 0.147 | 0.785 |

*(Continued)*

Table 1.1 – *Continued*

| Model | GRS | $p$(GRS) | $A\lvert\alpha_i\rvert$ | $\frac{A\lvert\alpha_i\rvert}{A\lvert\bar{r}_i\rvert}$ | $\frac{A\alpha_i^2}{A\bar{r}_i^2}$ | $\frac{As^2(\alpha_i)}{A\alpha_i^2}$ | $A(R^2)$ | $Sh^2(f)$ | $Sh_B^2(f)$ | $Sh^2(\alpha)$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | Panel C: 25 size-DR portfolios | | | | | | | | | |
| CAPM | 0.953 | 0.530 | 0.113 | 0.623 | 0.406 | 0.973 | 0.734 | 0.012 | 0.012 | 0.485 |
| FF3 | 2.074 | 0.002 | 0.130 | 0.714 | 0.758 | 0.255 | 0.867 | 0.043 | 0.032 | 0.545 |
| FFC | 1.948 | 0.004 | 0.106 | 0.583 | 0.353 | 0.499 | 0.881 | 0.086 | 0.054 | 0.772 |
| FFPS | 2.032 | 0.002 | 0.129 | 0.710 | 0.728 | 0.269 | 0.868 | 0.056 | 0.046 | 0.539 |
| FFAF | 1.984 | 0.003 | 0.105 | 0.577 | 0.506 | 0.327 | 0.880 | 0.027 | 0.026 | 0.521 |
| HXZ | 1.518 | 0.052 | 0.082 | 0.452 | 0.257 | 0.912 | 0.854 | 0.182 | 0.118 | 0.484 |
| FF5 | 1.807 | 0.010 | 0.108 | 0.591 | 0.493 | 0.393 | 0.875 | 0.107 | 0.078 | 0.493 |
| FF4 | 1.573 | 0.039 | 0.115 | 0.632 | 0.562 | 0.398 | 0.855 | 0.107 | 0.060 | 0.493 |
| SY4 | 1.900 | 0.006 | 0.093 | 0.513 | 0.298 | 0.755 | 0.869 | 0.233 | 0.112 | 0.595 |
| BS6 | 2.716 | 0.000 | 0.123 | 0.673 | 0.606 | 0.303 | 0.889 | 0.237 | 0.147 | 0.627 |
| | Panel D: 25 size-$\beta$ portfolios | | | | | | | | | |
| CAPM | 2.387 | 0.000 | 0.236 | 1.187 | 1.248 | 0.208 | 0.738 | 0.012 | 0.012 | 0.533 |
| FF3 | 1.788 | 0.011 | 0.129 | 0.646 | 0.425 | 0.272 | 0.870 | 0.043 | 0.032 | 0.662 |
| FFC | 1.341 | 0.125 | 0.082 | 0.411 | 0.186 | 0.632 | 0.873 | 0.086 | 0.054 | 0.667 |
| FFPS | 1.917 | 0.005 | 0.135 | 0.678 | 0.469 | 0.249 | 0.870 | 0.056 | 0.046 | 0.663 |
| FFAF | 2.149 | 0.001 | 0.185 | 0.929 | 0.758 | 0.161 | 0.857 | 0.027 | 0.026 | 0.598 |
| HXZ | 1.827 | 0.009 | 0.076 | 0.381 | 0.160 | 0.831 | 0.866 | 0.182 | 0.118 | 0.536 |
| FF5 | 1.857 | 0.007 | 0.083 | 0.415 | 0.179 | 0.621 | 0.881 | 0.107 | 0.078 | 0.855 |
| FF4 | 1.837 | 0.008 | 0.080 | 0.402 | 0.175 | 0.662 | 0.874 | 0.107 | 0.060 | 0.620 |
| SY4 | 1.217 | 0.216 | 0.063 | 0.319 | 0.103 | 1.457 | 0.861 | 0.233 | 0.112 | 0.424 |
| BS6 | 2.193 | 0.001 | 0.112 | 0.563 | 0.318 | 0.388 | 0.882 | 0.237 | 0.147 | 0.650 |
| | Panel E: 35 size-NI portfolios | | | | | | | | | |
| CAPM | 4.639 | 0.000 | 0.244 | 1.003 | 1.047 | 0.196 | 0.727 | 0.012 | 0.012 | 1.300 |
| FF3 | 4.115 | 0.000 | 0.148 | 0.606 | 0.557 | 0.175 | 0.863 | 0.043 | 0.032 | 1.406 |
| FFC | 3.653 | 0.000 | 0.134 | 0.551 | 0.451 | 0.224 | 0.864 | 0.086 | 0.054 | 1.381 |
| FFPS | 4.057 | 0.000 | 0.148 | 0.608 | 0.569 | 0.173 | 0.864 | 0.056 | 0.046 | 1.397 |
| FFAF | 4.477 | 0.000 | 0.183 | 0.752 | 0.757 | 0.132 | 0.856 | 0.027 | 0.026 | 1.369 |
| HXZ | 3.133 | 0.000 | 0.104 | 0.428 | 0.223 | 0.503 | 0.861 | 0.182 | 0.118 | 1.268 |
| FF5 | 3.324 | 0.000 | 0.110 | 0.450 | 0.241 | 0.386 | 0.877 | 0.107 | 0.078 | 1.466 |
| FF4 | 3.319 | 0.000 | 0.110 | 0.453 | 0.243 | 0.395 | 0.874 | 0.107 | 0.060 | 1.374 |
| SY4 | 2.780 | 0.000 | 0.109 | 0.446 | 0.251 | 0.496 | 0.858 | 0.233 | 0.112 | 1.180 |
| BS6 | 3.404 | 0.000 | 0.124 | 0.511 | 0.314 | 0.341 | 0.874 | 0.237 | 0.147 | 1.297 |
| | Panel F: 25 size-MAX portfolios | | | | | | | | | |
| CAPM | 7.867 | 0.000 | 0.318 | 1.142 | 1.296 | 0.094 | 0.754 | 0.012 | 0.012 | 0.947 |
| FF3 | 7.165 | 0.000 | 0.221 | 0.792 | 0.741 | 0.083 | 0.862 | 0.043 | 0.032 | 0.965 |
| FFC | 6.725 | 0.000 | 0.208 | 0.748 | 0.614 | 0.100 | 0.866 | 0.086 | 0.054 | 1.054 |
| FFPS | 7.157 | 0.000 | 0.220 | 0.788 | 0.737 | 0.085 | 0.863 | 0.056 | 0.046 | 0.955 |
| FFAF | 7.673 | 0.000 | 0.269 | 0.967 | 1.020 | 0.060 | 0.857 | 0.027 | 0.026 | 1.003 |
| HXZ | 6.097 | 0.000 | 0.152 | 0.547 | 0.324 | 0.214 | 0.861 | 0.182 | 0.118 | 0.867 |
| FF5 | 6.377 | 0.000 | 0.147 | 0.526 | 0.331 | 0.166 | 0.885 | 0.107 | 0.078 | 0.992 |
| FF4 | 6.356 | 0.000 | 0.145 | 0.521 | 0.325 | 0.178 | 0.878 | 0.107 | 0.060 | 0.895 |
| SY4 | 5.445 | 0.000 | 0.141 | 0.507 | 0.275 | 0.265 | 0.863 | 0.233 | 0.112 | 0.888 |
| BS6 | 6.074 | 0.000 | 0.150 | 0.537 | 0.261 | 0.235 | 0.884 | 0.237 | 0.147 | 0.982 |

*(Continued)*

Table 1.1 – *Continued*

| Model | GRS | $p$(GRS) | $A\lvert\alpha_i\rvert$ | $\frac{A\lvert\alpha_i\rvert}{A\lvert\bar{r}_i\rvert}$ | $\frac{A\alpha_i^2}{A\bar{r}_i^2}$ | $\frac{As^2(\alpha_i)}{A\alpha_i^2}$ | $A(R^2)$ | $Sh^2(f)$ | $Sh_B^2(f)$ | $Sh^2(\alpha)$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | Panel G: 25 size-RVar portfolios | | | | | | | | | |
| CAPM | 6.835 | 0.000 | 0.361 | 1.157 | 1.384 | 0.078 | 0.746 | 0.012 | 0.012 | 1.149 |
| FF3 | 6.738 | 0.000 | 0.240 | 0.770 | 0.989 | 0.055 | 0.865 | 0.043 | 0.032 | 1.216 |
| FFC | 6.019 | 0.000 | 0.221 | 0.710 | 0.660 | 0.079 | 0.870 | 0.086 | 0.054 | 1.207 |
| FFPS | 6.678 | 0.000 | 0.243 | 0.779 | 0.996 | 0.055 | 0.865 | 0.056 | 0.046 | 1.203 |
| FFAF | 7.514 | 0.000 | 0.305 | 0.978 | 1.306 | 0.041 | 0.855 | 0.027 | 0.026 | 1.222 |
| HXZ | 5.623 | 0.000 | 0.123 | 0.395 | 0.213 | 0.273 | 0.863 | 0.182 | 0.118 | 1.038 |
| FF5 | 6.049 | 0.000 | 0.139 | 0.445 | 0.405 | 0.113 | 0.893 | 0.107 | 0.078 | 1.194 |
| FF4 | 6.058 | 0.000 | 0.137 | 0.440 | 0.406 | 0.122 | 0.881 | 0.107 | 0.060 | 1.123 |
| SY4 | 5.813 | 0.000 | 0.116 | 0.373 | 0.232 | 0.271 | 0.866 | 0.233 | 0.112 | 1.072 |
| BS6 | 6.427 | 0.000 | 0.143 | 0.458 | 0.228 | 0.214 | 0.892 | 0.237 | 0.147 | 1.023 |
| | Panel H: 25 size-AC portfolios | | | | | | | | | |
| CAPM | 3.865 | 0.000 | 0.147 | 0.821 | 0.657 | 0.485 | 0.759 | 0.012 | 0.012 | 0.725 |
| FF3 | 3.935 | 0.000 | 0.113 | 0.634 | 0.458 | 0.263 | 0.902 | 0.043 | 0.032 | 0.877 |
| FFC | 3.485 | 0.000 | 0.110 | 0.614 | 0.394 | 0.316 | 0.902 | 0.086 | 0.054 | 0.882 |
| FFPS | 3.781 | 0.000 | 0.109 | 0.613 | 0.434 | 0.279 | 0.902 | 0.056 | 0.046 | 0.869 |
| FFAF | 3.870 | 0.000 | 0.116 | 0.650 | 0.477 | 0.249 | 0.901 | 0.027 | 0.026 | 0.833 |
| HXZ | 3.693 | 0.000 | 0.134 | 0.749 | 0.570 | 0.238 | 0.904 | 0.182 | 0.118 | 0.805 |
| FF5 | 4.186 | 0.000 | 0.117 | 0.656 | 0.468 | 0.251 | 0.910 | 0.107 | 0.078 | 0.910 |
| FF4 | 4.032 | 0.000 | 0.118 | 0.664 | 0.475 | 0.249 | 0.909 | 0.107 | 0.060 | 0.846 |
| SY4 | 2.818 | 0.000 | 0.095 | 0.530 | 0.328 | 0.495 | 0.889 | 0.233 | 0.112 | 0.812 |
| BS6 | 4.750 | 0.000 | 0.137 | 0.768 | 0.608 | 0.218 | 0.909 | 0.237 | 0.147 | 0.964 |
| | Panel I: 30 IND portfolios | | | | | | | | | |
| CAPM | 1.311 | 0.127 | 0.150 | 1.173 | 1.630 | 0.669 | 0.578 | 0.012 | 0.012 | 0.650 |
| FF3 | 2.284 | 0.000 | 0.206 | 1.604 | 2.527 | 0.409 | 0.614 | 0.043 | 0.032 | 0.672 |
| FFC | 2.395 | 0.000 | 0.174 | 1.356 | 1.928 | 0.551 | 0.619 | 0.086 | 0.054 | 0.808 |
| FFPS | 2.339 | 0.000 | 0.217 | 1.692 | 2.870 | 0.361 | 0.618 | 0.056 | 0.046 | 0.667 |
| FFAF | 1.774 | 0.007 | 0.183 | 1.425 | 2.260 | 0.449 | 0.614 | 0.027 | 0.026 | 0.692 |
| HXZ | 2.395 | 0.000 | 0.207 | 1.618 | 2.387 | 0.489 | 0.618 | 0.182 | 0.118 | 0.675 |
| FF5 | 2.644 | 0.000 | 0.243 | 1.899 | 3.033 | 0.340 | 0.643 | 0.107 | 0.078 | 0.622 |
| FF4 | 2.282 | 0.000 | 0.249 | 1.944 | 3.170 | 0.332 | 0.633 | 0.107 | 0.060 | 0.623 |
| SY4 | 1.971 | 0.002 | 0.180 | 1.401 | 1.774 | 0.691 | 0.615 | 0.233 | 0.112 | 0.684 |
| BS6 | 4.530 | 0.000 | 0.298 | 2.327 | 4.545 | 0.254 | 0.641 | 0.237 | 0.147 | 0.735 |
| | Panel J: 8 D10−1 portfolios | | | | | | | | | |
| CAPM | 9.964 | 0.000 | 0.547 | 0.647 | 0.557 | 0.079 | 0.192 | 0.012 | 0.012 | 0.052 |
| FF3 | 12.860 | 0.000 | 0.577 | 0.683 | 0.545 | 0.057 | 0.361 | 0.043 | 0.032 | 0.057 |
| FFC | 10.194 | 0.000 | 0.464 | 0.549 | 0.332 | 0.090 | 0.403 | 0.086 | 0.054 | 0.044 |
| FFPS | 12.805 | 0.000 | 0.580 | 0.686 | 0.557 | 0.056 | 0.363 | 0.056 | 0.046 | 0.058 |
| FFAF | 14.790 | 0.000 | 0.623 | 0.737 | 0.668 | 0.046 | 0.368 | 0.027 | 0.026 | 0.075 |
| HXZ | 5.940 | 0.000 | 0.262 | 0.310 | 0.109 | 0.308 | 0.381 | 0.182 | 0.118 | 0.022 |
| FF5 | 8.317 | 0.000 | 0.362 | 0.429 | 0.189 | 0.154 | 0.411 | 0.107 | 0.078 | 0.019 |
| FF4 | 8.183 | 0.000 | 0.365 | 0.432 | 0.192 | 0.161 | 0.386 | 0.107 | 0.060 | 0.020 |
| SY4 | 4.347 | 0.000 | 0.259 | 0.307 | 0.120 | 0.280 | 0.414 | 0.233 | 0.112 | 0.033 |
| BS6 | 7.153 | 0.000 | 0.270 | 0.320 | 0.133 | 0.240 | 0.431 | 0.237 | 0.147 | 0.045 |

## Table 1.2: Overall performance of factor models in time-series (absolute) tests

The table reports overall performance in time-series (absolute) tests of ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. NGRS, N$A|\alpha_i|$, N$A|\alpha_i|/A|\overline{r}_i|$, N$A\alpha_i^2/A\overline{r}_i^2$, N$As^2(\alpha_i)/A\alpha_i^2$, N$A(R^2)$, and N$Sh^2(\alpha)$ are the number of the sets of anomaly portfolios across which a given factor model produces, respectively, the smallest $F$-statistic of the Gibbons, Ross, and Shanken (1989) test, the smallest value of $A|\alpha_i|$, the smallest value of $A|\alpha_i|/A|\overline{r}_i|$, the smallest value of $A\alpha_i^2/A\overline{r}_i^2$, the largest value of $As^2(\alpha_i)/A\alpha_i^2$, the largest value of $A(R^2)$, and the smallest value of $Sh^2(\alpha)$. NSTR, NCI, NDR, N$\beta$, NNI, NMAX, NRVar, NAC, NIND, and ND10−1 are the number of statistically significant alphas (i.e., with a Newey and West (1987)-adjusted $t$-statistic $\geqslant 2.00$), respectively, across the 25 size-STR (short-term reversal) portfolios, the 25 size-CI (abnormal capital investment) portfolios, the 25 size-DR (distress risk) portfolios, the 25 size-$\beta$ (market beta) portfolios, the 35 size-NI (net share issues) portfolios, the 25 size-MAX (lottery demand) portfolios, the 25 size-RVar (residual variance) portfolios, the 25 size-AC (accruals) portfolios, the 30 IND (industry) portfolios, and the 8 D10−1 (high minus low decile) portfolios relative to a given factor model. NMicro is the number of statistically significant alphas (i.e., with a Newey and West (1987)-adjusted $t$-statistic $\geqslant 2.00$) on the 42 smallest size (i.e., microcap) portfolios relative to a given factor model. The sample period is from January 1968 to December 2016. See also notes to Table 1.1.

| Model | NGRS | N$A\|\alpha_i\|$ | N$\frac{A\|\alpha_i\|}{A\|\overline{r}_i\|}$ | N$\frac{A\alpha_i^2}{A\overline{r}_i^2}$ | N$\frac{As^2(\alpha_i)}{A\alpha_i^2}$ | N$A(R^2)$ | N$Sh^2(\alpha)$ | NSTR | NCI | NDR | N$\beta$ | NNI | NMAX | NRVar | NAC | NIND | ND10−1 | NMicro |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CAPM | 2 | 1 | 1 | 1 | 2 | 0 | 1 | 10 | 9 | 0 | 12 | 15 | 14 | 17 | 4 | 4 | 5 | 15 |
| FF3 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 6 | 4 | 7 | 7 | 11 | 12 | 13 | 10 | 9 | 6 | 16 |
| FFC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 14 | 4 | 3 | 13 | 14 | 14 | 8 | 7 | 5 | 19 |
| FFPS | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 6 | 4 | 8 | 10 | 11 | 11 | 14 | 7 | 9 | 6 | 16 |
| FFAF | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 7 | 3 | 6 | 13 | 15 | 15 | 14 | 9 | 7 | 7 | 19 |
| HXZ | 1 | 2 | 2 | 4 | 3 | 0 | 2 | 8 | 4 | 0 | 2 | 5 | 4 | 4 | 7 | 7 | 2 | 12 |
| FF5 | 0 | 0 | 0 | 0 | 0 | 5 | 2 | 9 | 4 | 5 | 2 | 7 | 8 | 5 | 10 | 10 | 6 | 12 |
| FF4 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 8 | 4 | 3 | 2 | 7 | 8 | 4 | 10 | 10 | 6 | 12 |
| SY4 | 5 | 5 | 5 | 2 | 4 | 0 | 2 | 11 | 4 | 3 | 0 | 3 | 6 | 4 | 3 | 4 | 2 | 11 |
| BS6 | 1 | 0 | 0 | 2 | 0 | 5 | 1 | 5 | 2 | 7 | 4 | 7 | 8 | 5 | 5 | 11 | 3 | 10 |

Table 1.3: Tests of equality of cross-sectional $R^2$s: 25 size-STR portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-STR (short-term reversal) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.577 | −0.582 | −0.622 | −0.487 | −0.510 | −0.627 | −0.573 | −0.553 | −0.660 |
| | (0.046) | (0.062) | (0.132) | (0.021) | (0.128) | (0.098) | (0.049) | (0.066) | (0.023) |
| FF3 | | −0.006 | −0.046 | 0.090 | 0.066 | −0.050 | 0.004 | 0.024 | −0.083 |
| | | (0.649) | (0.155) | (0.195) | (0.693) | (0.319) | (0.972) | (0.667) | (0.259) |
| FFC | | | −0.040 | 0.096 | 0.072 | −0.045 | 0.010 | 0.030 | −0.077 |
| | | | (0.554) | (0.203) | (0.638) | (0.357) | (0.925) | (0.540) | (0.300) |
| FFPS | | | | 0.135 | 0.112 | −0.005 | 0.050 | 0.069 | 0.000 |
| | | | | (0.170) | (0.564) | (0.945) | (0.729) | (0.408) | (0.617) |
| FFAF | | | | | −0.023 | −0.140 | −0.086 | −0.066 | −0.173 |
| | | | | | (0.878) | (0.113) | (0.475) | (0.432) | (0.087) |
| HXZ | | | | | | −0.117 | −0.062 | −0.042 | −0.149 |
| | | | | | | (0.494) | (0.528) | (0.774) | (0.411) |
| FF5 | | | | | | | 0.055 | 0.074 | −0.033 |
| | | | | | | | (0.295) | (0.284) | (0.431) |
| FF4 | | | | | | | | 0.020 | −0.087 |
| | | | | | | | | (0.852) | (0.465) |
| SY4 | | | | | | | | | −0.107 |
| | | | | | | | | | (0.238) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.213 | −0.221 | −0.304 | −0.193 | −0.115 | −0.277 | −0.190 | −0.163 | −0.474 |
| | (0.009) | (0.025) | (0.040) | (0.004) | (0.180) | (0.083) | (0.046) | (0.063) | (0.014) |
| FF3 | | −0.008 | −0.091 | 0.020 | 0.097 | −0.064 | 0.023 | 0.049 | −0.261 |
| | | (0.567) | (0.171) | (0.787) | (0.449) | (0.506) | (0.838) | (0.527) | (0.161) |
| FFC | | | −0.083 | 0.028 | 0.106 | −0.056 | 0.031 | 0.058 | −0.252 |
| | | | (0.512) | (0.600) | (0.454) | (0.565) | (0.792) | (0.448) | (0.151) |
| FFPS | | | | 0.111 | 0.189 | 0.027 | 0.114 | 0.141 | −0.170 |
| | | | | (0.454) | (0.259) | (0.835) | (0.458) | (0.348) | (0.401) |
| FFAF | | | | | 0.078 | −0.084 | 0.003 | 0.030 | −0.280 |
| | | | | | (0.588) | (0.470) | (0.978) | (0.704) | (0.101) |
| HXZ | | | | | | −0.161 | −0.074 | −0.048 | −0.358 |
| | | | | | | (0.318) | (0.391) | (0.724) | (0.095) |
| FF5 | | | | | | | 0.087 | 0.113 | −0.197 |
| | | | | | | | (0.143) | (0.405) | (0.135) |
| FF4 | | | | | | | | 0.026 | −0.284 |
| | | | | | | | | (0.834) | (0.096) |
| SY4 | | | | | | | | | −0.310 |
| | | | | | | | | | (0.129) |

Table 1.4: Tests of equality of cross-sectional $R^2$s: 25 size-CI portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-CI (abnormal capital investment) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.352 | −0.482 | −0.365 | −0.301 | −0.403 | −0.352 | −0.352 | −0.442 | −0.486 |
| | (0.023) | (0.150) | (0.036) | (0.034) | (0.048) | (0.043) | (0.036) | (0.052) | (0.141) |
| FF3 | | −0.130 | −0.013 | 0.051 | −0.051 | 0.000 | 0.001 | −0.090 | −0.134 |
| | | (0.035) | (0.398) | (0.230) | (0.431) | (0.984) | (0.982) | (0.225) | (0.151) |
| FFC | | | 0.117 | 0.181 | 0.079 | 0.130 | 0.131 | 0.040 | −0.003 |
| | | | (0.200) | (0.077) | (0.298) | (0.136) | (0.128) | (0.449) | (0.924) |
| FFPS | | | | 0.064 | −0.038 | 0.013 | 0.013 | −0.077 | 0.000 |
| | | | | (0.258) | (0.532) | (0.686) | (0.693) | (0.326) | (0.228) |
| FFAF | | | | | −0.102 | −0.051 | −0.050 | −0.141 | −0.185 |
| | | | | | (0.243) | (0.304) | (0.336) | (0.114) | (0.076) |
| HXZ | | | | | | 0.050 | 0.051 | −0.039 | −0.083 |
| | | | | | | (0.330) | (0.287) | (0.513) | (0.323) |
| FF5 | | | | | | | 0.001 | −0.090 | −0.133 |
| | | | | | | | (0.831) | (0.181) | (0.140) |
| FF4 | | | | | | | | −0.090 | −0.134 |
| | | | | | | | | (0.164) | (0.135) |
| SY4 | | | | | | | | | −0.044 |
| | | | | | | | | | (0.463) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.273 | −0.507 | −0.300 | −0.127 | −0.383 | −0.297 | −0.287 | −0.467 | −0.474 |
| | (0.002) | (0.009) | (0.010) | (0.045) | (0.008) | (0.036) | (0.013) | (0.004) | (0.032) |
| FF3 | | −0.233 | −0.026 | 0.146 | −0.110 | −0.023 | −0.014 | −0.193 | −0.201 |
| | | (0.025) | (0.359) | (0.072) | (0.378) | (0.704) | (0.875) | (0.179) | (0.224) |
| FFC | | | 0.207 | 0.379 | 0.124 | 0.210 | 0.220 | 0.040 | 0.032 |
| | | | (0.242) | (0.051) | (0.425) | (0.164) | (0.150) | (0.719) | (0.586) |
| FFPS | | | | 0.172 | −0.084 | 0.003 | 0.013 | −0.167 | −0.175 |
| | | | | (0.097) | (0.501) | (0.969) | (0.896) | (0.290) | (0.323) |
| FFAF | | | | | −0.256 | −0.169 | −0.160 | −0.339 | −0.347 |
| | | | | | (0.079) | (0.122) | (0.169) | (0.043) | (0.067) |
| HXZ | | | | | | 0.087 | 0.096 | −0.084 | −0.091 |
| | | | | | | (0.451) | (0.339) | (0.530) | (0.490) |
| FF5 | | | | | | | 0.010 | −0.170 | −0.178 |
| | | | | | | | (0.604) | (0.218) | (0.247) |
| FF4 | | | | | | | | −0.180 | −0.187 |
| | | | | | | | | (0.176) | (0.206) |
| SY4 | | | | | | | | | −0.008 |
| | | | | | | | | | (0.941) |

Table 1.5: Tests of equality of cross-sectional $R^2$s: 25 size-DR portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-DR (distress risk) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.217 | −0.297 | −0.219 | −0.251 | −0.246 | −0.252 | −0.187 | −0.270 | −0.298 |
| | (0.495) | (0.561) | (0.573) | (0.454) | (0.536) | (0.611) | (0.658) | (0.513) | (0.712) |
| FF3 | | −0.081 | −0.002 | −0.034 | −0.029 | −0.035 | 0.029 | −0.053 | −0.081 |
| | | (0.235) | (0.831) | (0.489) | (0.782) | (0.684) | (0.682) | (0.571) | (0.502) |
| FFC | | | 0.078 | 0.047 | 0.051 | 0.045 | 0.110 | 0.027 | −0.001 |
| | | | (0.569) | (0.607) | (0.519) | (0.744) | (0.365) | (0.761) | (0.967) |
| FFPS | | | | −0.032 | −0.027 | −0.033 | 0.032 | −0.051 | 0.000 |
| | | | | (0.597) | (0.810) | (0.706) | (0.674) | (0.604) | (0.522) |
| FFAF | | | | | 0.005 | −0.001 | 0.063 | −0.019 | −0.048 |
| | | | | | (0.951) | (0.988) | (0.405) | (0.786) | (0.584) |
| HXZ | | | | | | −0.006 | 0.059 | −0.024 | −0.052 |
| | | | | | | (0.962) | (0.413) | (0.781) | (0.550) |
| FF5 | | | | | | | 0.065 | −0.018 | −0.046 |
| | | | | | | | (0.232) | (0.790) | (0.711) |
| FF4 | | | | | | | | −0.083 | −0.111 |
| | | | | | | | | (0.410) | (0.364) |
| SY4 | | | | | | | | | −0.028 |
| | | | | | | | | | (0.722) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.086 | −0.242 | −0.088 | −0.133 | −0.148 | −0.102 | −0.058 | −0.149 | −0.256 |
| | (0.431) | (0.362) | (0.650) | (0.278) | (0.452) | (0.779) | (0.800) | (0.430) | (0.632) |
| FF3 | | −0.156 | −0.002 | −0.047 | −0.062 | −0.016 | 0.028 | −0.063 | −0.170 |
| | | (0.191) | (0.861) | (0.396) | (0.610) | (0.805) | (0.647) | (0.605) | (0.432) |
| FFC | | | 0.154 | 0.109 | 0.094 | 0.140 | 0.184 | 0.093 | −0.014 |
| | | | (0.453) | (0.521) | (0.579) | (0.483) | (0.371) | (0.538) | (0.818) |
| FFPS | | | | −0.045 | −0.060 | −0.015 | 0.029 | −0.062 | −0.169 |
| | | | | (0.479) | (0.638) | (0.834) | (0.646) | (0.622) | (0.445) |
| FFAF | | | | | −0.015 | 0.030 | 0.074 | −0.017 | −0.124 |
| | | | | | (0.878) | (0.707) | (0.415) | (0.876) | (0.518) |
| HXZ | | | | | | 0.046 | 0.090 | −0.001 | −0.108 |
| | | | | | | (0.721) | (0.421) | (0.990) | (0.550) |
| FF5 | | | | | | | 0.044 | −0.047 | −0.154 |
| | | | | | | | (0.404) | (0.637) | (0.494) |
| FF4 | | | | | | | | −0.091 | −0.198 |
| | | | | | | | | (0.496) | (0.351) |
| SY4 | | | | | | | | | −0.107 |
| | | | | | | | | | (0.539) |

Table 1.6: Tests of equality of cross-sectional $R^2$s: 25 size-$\beta$ portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-$\beta$ (market beta) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.693 | −0.785 | −0.710 | −0.554 | −0.743 | −0.749 | −0.745 | −0.750 | −0.778 |
| | (0.071) | (0.099) | (0.096) | (0.113) | (0.039) | (0.044) | (0.034) | (0.045) | (0.072) |
| FF3 | | −0.091 | −0.016 | 0.139 | −0.050 | −0.056 | −0.052 | −0.057 | −0.084 |
| | | (0.063) | (0.321) | (0.200) | (0.539) | (0.427) | (0.524) | (0.575) | (0.368) |
| FFC | | | 0.075 | 0.231 | 0.041 | 0.035 | 0.040 | 0.034 | 0.007 |
| | | | (0.351) | (0.155) | (0.569) | (0.590) | (0.563) | (0.682) | (0.864) |
| FFPS | | | | 0.156 | −0.034 | −0.039 | −0.035 | −0.041 | 0.000 |
| | | | | (0.202) | (0.612) | (0.484) | (0.590) | (0.662) | (0.426) |
| FFAF | | | | | −0.189 | −0.195 | −0.191 | −0.196 | −0.224 |
| | | | | | (0.234) | (0.205) | (0.225) | (0.231) | (0.171) |
| HXZ | | | | | | −0.006 | −0.001 | −0.007 | −0.034 |
| | | | | | | (0.865) | (0.965) | (0.938) | (0.569) |
| FF5 | | | | | | | 0.004 | −0.001 | −0.028 |
| | | | | | | | (0.594) | (0.987) | (0.642) |
| FF4 | | | | | | | | −0.006 | −0.033 |
| | | | | | | | | (0.937) | (0.587) |
| SY4 | | | | | | | | | −0.027 |
| | | | | | | | | | (0.767) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.218 | −0.443 | −0.246 | −0.070 | −0.337 | −0.325 | −0.323 | −0.429 | −0.448 |
| | (0.021) | (0.029) | (0.047) | (0.347) | (0.013) | (0.028) | (0.013) | (0.009) | (0.051) |
| FF3 | | −0.225 | −0.028 | 0.148 | −0.119 | −0.107 | −0.105 | −0.212 | −0.230 |
| | | (0.051) | (0.365) | (0.175) | (0.372) | (0.324) | (0.373) | (0.249) | (0.255) |
| FFC | | | 0.198 | 0.373 | 0.106 | 0.118 | 0.120 | 0.014 | −0.004 |
| | | | (0.320) | (0.102) | (0.537) | (0.546) | (0.542) | (0.940) | (0.954) |
| FFPS | | | | 0.175 | −0.091 | −0.079 | −0.077 | −0.184 | −0.202 |
| | | | | (0.165) | (0.476) | (0.465) | (0.505) | (0.321) | (0.325) |
| FFAF | | | | | −0.267 | −0.255 | −0.253 | −0.359 | −0.377 |
| | | | | | (0.100) | (0.089) | (0.091) | (0.054) | (0.088) |
| HXZ | | | | | | 0.012 | 0.014 | −0.093 | −0.111 |
| | | | | | | (0.883) | (0.859) | (0.544) | (0.468) |
| FF5 | | | | | | | 0.002 | −0.105 | −0.123 |
| | | | | | | | (0.784) | (0.450) | (0.517) |
| FF4 | | | | | | | | −0.107 | −0.125 |
| | | | | | | | | (0.425) | (0.509) |
| SY4 | | | | | | | | | −0.018 |
| | | | | | | | | | (0.916) |

Table 1.7: Tests of equality of cross-sectional $R^2$s: 35 size-NI portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 35 size-NI (net share issues) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.438 | −0.641 | −0.463 | −0.315 | −0.645 | −0.607 | −0.596 | −0.660 | −0.665 |
| | (0.006) | (0.055) | (0.016) | (0.017) | (0.004) | (0.004) | (0.005) | (0.003) | (0.020) |
| FF3 | | −0.203 | −0.025 | 0.124 | −0.206 | −0.169 | −0.158 | −0.222 | −0.227 |
| | | (0.009) | (0.349) | (0.047) | (0.011) | (0.025) | (0.031) | (0.015) | (0.020) |
| FFC | | | 0.178 | 0.326 | −0.004 | 0.034 | 0.045 | −0.019 | −0.024 |
| | | | (0.070) | (0.010) | (0.964) | (0.734) | (0.677) | (0.792) | (0.700) |
| FFPS | | | | 0.148 | −0.182 | −0.144 | −0.133 | −0.197 | 0.001 |
| | | | | (0.064) | (0.052) | (0.109) | (0.134) | (0.045) | (0.037) |
| FFAF | | | | | −0.330 | −0.292 | −0.282 | −0.345 | −0.350 |
| | | | | | (0.004) | (0.008) | (0.013) | (0.003) | (0.004) |
| HXZ | | | | | | 0.038 | 0.048 | −0.015 | −0.020 |
| | | | | | | (0.434) | (0.365) | (0.817) | (0.689) |
| FF5 | | | | | | | 0.011 | −0.053 | −0.058 |
| | | | | | | | (0.412) | (0.404) | (0.416) |
| FF4 | | | | | | | | −0.064 | −0.069 |
| | | | | | | | | (0.427) | (0.415) |
| SY4 | | | | | | | | | −0.005 |
| | | | | | | | | | (0.922) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.094 | −0.278 | −0.101 | −0.029 | −0.307 | −0.226 | −0.223 | −0.336 | −0.329 |
| | (0.007) | (0.013) | (0.108) | (0.207) | (0.000) | (0.004) | (0.001) | (0.000) | (0.016) |
| FF3 | | −0.184 | −0.008 | 0.065 | −0.214 | −0.132 | −0.130 | −0.242 | −0.235 |
| | | (0.019) | (0.605) | (0.128) | (0.023) | (0.075) | (0.068) | (0.018) | (0.053) |
| FFC | | | 0.177 | 0.249 | −0.029 | 0.052 | 0.055 | −0.058 | −0.051 |
| | | | (0.151) | (0.067) | (0.797) | (0.702) | (0.689) | (0.589) | (0.513) |
| FFPS | | | | 0.072 | −0.206 | −0.125 | −0.122 | −0.235 | −0.227 |
| | | | | (0.155) | (0.041) | (0.132) | (0.127) | (0.027) | (0.066) |
| FFAF | | | | | −0.278 | −0.197 | −0.194 | −0.307 | −0.300 |
| | | | | | (0.006) | (0.014) | (0.017) | (0.003) | (0.018) |
| HXZ | | | | | | 0.081 | 0.084 | −0.029 | −0.021 |
| | | | | | | (0.229) | (0.223) | (0.729) | (0.742) |
| FF5 | | | | | | | 0.003 | −0.110 | −0.103 |
| | | | | | | | (0.681) | (0.180) | (0.329) |
| FF4 | | | | | | | | −0.113 | −0.105 |
| | | | | | | | | (0.196) | (0.333) |
| SY4 | | | | | | | | | 0.007 |
| | | | | | | | | | (0.931) |

Table 1.8: Tests of equality of cross-sectional $R^2$s: 25 size-MAX portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-MAX (lottery demand) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.313 | −0.383 | −0.315 | −0.212 | −0.345 | −0.366 | −0.354 | −0.359 | −0.393 |
| | (0.007) | (0.039) | (0.011) | (0.023) | (0.009) | (0.056) | (0.012) | (0.007) | (0.034) |
| FF3 | | −0.069 | −0.002 | 0.101 | −0.032 | −0.052 | −0.041 | −0.046 | −0.080 |
| | | (0.091) | (0.691) | (0.108) | (0.572) | (0.424) | (0.469) | (0.301) | (0.231) |
| FFC | | | 0.067 | 0.170 | 0.037 | 0.017 | 0.028 | 0.023 | −0.011 |
| | | | (0.213) | (0.061) | (0.458) | (0.829) | (0.656) | (0.554) | (0.830) |
| FFPS | | | | 0.103 | −0.030 | −0.050 | −0.039 | −0.044 | 0.001 |
| | | | | (0.088) | (0.603) | (0.445) | (0.497) | (0.342) | (0.238) |
| FFAF | | | | | −0.133 | −0.153 | −0.142 | −0.147 | −0.181 |
| | | | | | (0.123) | (0.070) | (0.080) | (0.081) | (0.040) |
| HXZ | | | | | | −0.020 | −0.009 | −0.014 | −0.048 |
| | | | | | | (0.764) | (0.824) | (0.760) | (0.369) |
| FF5 | | | | | | | 0.011 | 0.007 | −0.028 |
| | | | | | | | (0.544) | (0.931) | (0.661) |
| FF4 | | | | | | | | −0.005 | −0.039 |
| | | | | | | | | (0.932) | (0.456) |
| SY4 | | | | | | | | | −0.034 |
| | | | | | | | | | (0.554) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.107 | −0.219 | −0.110 | −0.024 | −0.229 | −0.245 | −0.238 | −0.293 | −0.263 |
| | (0.003) | (0.032) | (0.040) | (0.371) | (0.004) | (0.058) | (0.015) | (0.002) | (0.169) |
| FF3 | | −0.113 | −0.003 | 0.082 | −0.122 | −0.138 | −0.132 | −0.186 | −0.156 |
| | | (0.092) | (0.682) | (0.093) | (0.243) | (0.167) | (0.145) | (0.053) | (0.121) |
| FFC | | | 0.109 | 0.195 | −0.009 | −0.025 | −0.019 | −0.074 | −0.044 |
| | | | (0.357) | (0.157) | (0.924) | (0.838) | (0.881) | (0.416) | (0.651) |
| FFPS | | | | 0.086 | −0.119 | −0.135 | −0.128 | −0.183 | −0.153 |
| | | | | (0.110) | (0.251) | (0.172) | (0.148) | (0.058) | (0.126) |
| FFAF | | | | | −0.205 | −0.221 | −0.214 | −0.269 | −0.239 |
| | | | | | (0.048) | (0.015) | (0.010) | (0.016) | (0.017) |
| HXZ | | | | | | −0.016 | −0.010 | −0.064 | −0.034 |
| | | | | | | (0.777) | (0.889) | (0.474) | (0.328) |
| FF5 | | | | | | | 0.007 | −0.048 | −0.018 |
| | | | | | | | (0.681) | (0.607) | (0.746) |
| FF4 | | | | | | | | −0.055 | −0.025 |
| | | | | | | | | (0.594) | (0.670) |
| SY4 | | | | | | | | | 0.030 |
| | | | | | | | | | (0.742) |

Table 1.9: Tests of equality of cross-sectional $R^2$s: 25 size-RVar portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-RVar (residual variance) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.296 | −0.481 | −0.314 | −0.096 | −0.542 | −0.580 | −0.580 | −0.520 | −0.579 |
| | (0.006) | (0.071) | (0.019) | (0.162) | (0.002) | (0.017) | (0.008) | (0.013) | (0.013) |
| FF3 | | −0.185 | −0.018 | 0.200 | −0.246 | −0.285 | −0.284 | −0.224 | −0.283 |
| | | (0.048) | (0.409) | (0.069) | (0.034) | (0.012) | (0.011) | (0.054) | (0.010) |
| FFC | | | 0.167 | 0.385 | −0.061 | −0.099 | −0.099 | −0.039 | −0.098 |
| | | | (0.136) | (0.025) | (0.291) | (0.166) | (0.160) | (0.417) | (0.152) |
| FFPS | | | | 0.218 | −0.228 | −0.267 | −0.266 | −0.206 | 0.003 |
| | | | | (0.089) | (0.061) | (0.024) | (0.023) | (0.094) | (0.017) |
| FFAF | | | | | −0.446 | −0.485 | −0.484 | −0.424 | −0.483 |
| | | | | | (0.006) | (0.003) | (0.003) | (0.011) | (0.004) |
| HXZ | | | | | | −0.039 | −0.038 | 0.022 | −0.037 |
| | | | | | | (0.388) | (0.360) | (0.489) | (0.341) |
| FF5 | | | | | | | 0.001 | 0.060 | 0.002 |
| | | | | | | | (0.863) | (0.207) | (0.963) |
| FF4 | | | | | | | | 0.060 | 0.001 |
| | | | | | | | | (0.180) | (0.972) |
| SY4 | | | | | | | | | −0.059 |
| | | | | | | | | | (0.241) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.028 | −0.051 | −0.030 | −0.006 | −0.266 | −0.450 | −0.449 | −0.170 | −0.392 |
| | (0.220) | (0.400) | (0.495) | (0.778) | (0.001) | (0.006) | (0.001) | (0.040) | (0.013) |
| FF3 | | −0.023 | −0.003 | 0.021 | −0.238 | −0.422 | −0.422 | −0.143 | −0.364 |
| | | (0.431) | (0.725) | (0.452) | (0.069) | (0.012) | (0.010) | (0.273) | (0.019) |
| FFC | | | 0.020 | 0.045 | −0.215 | −0.399 | −0.398 | −0.119 | −0.341 |
| | | | (0.718) | (0.475) | (0.051) | (0.016) | (0.015) | (0.228) | (0.037) |
| FFPS | | | | 0.024 | −0.235 | −0.420 | −0.419 | −0.140 | −0.361 |
| | | | | (0.422) | (0.075) | (0.011) | (0.010) | (0.277) | (0.021) |
| FFAF | | | | | −0.259 | −0.444 | −0.443 | −0.164 | −0.386 |
| | | | | | (0.035) | (0.007) | (0.006) | (0.183) | (0.012) |
| HXZ | | | | | | −0.184 | −0.184 | 0.095 | −0.126 |
| | | | | | | (0.137) | (0.127) | (0.190) | (0.250) |
| FF5 | | | | | | | 0.001 | 0.280 | 0.058 |
| | | | | | | | (0.878) | (0.035) | (0.556) |
| FF4 | | | | | | | | 0.279 | 0.057 |
| | | | | | | | | (0.031) | (0.559) |
| SY4 | | | | | | | | | −0.222 |
| | | | | | | | | | (0.131) |

Table 1.10: Tests of equality of cross-sectional $R^2$s: 25 size-AC portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 25 size-AC (accruals) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.360 | −0.639 | −0.382 | −0.335 | −0.494 | −0.584 | −0.551 | −0.489 | −0.680 |
| | (0.093) | (0.201) | (0.144) | (0.121) | (0.079) | (0.048) | (0.025) | (0.106) | (0.202) |
| FF3 | | −0.279 | −0.022 | 0.025 | −0.134 | −0.224 | −0.191 | −0.129 | −0.320 |
| | | (0.007) | (0.568) | (0.504) | (0.092) | (0.100) | (0.099) | (0.179) | (0.083) |
| FFC | | | 0.257 | 0.304 | 0.145 | 0.055 | 0.088 | 0.150 | −0.041 |
| | | | (0.185) | (0.143) | (0.420) | (0.717) | (0.556) | (0.412) | (0.459) |
| FFPS | | | | 0.047 | −0.112 | −0.202 | −0.169 | −0.107 | 0.001 |
| | | | | (0.557) | (0.340) | (0.168) | (0.203) | (0.340) | (0.098) |
| FFAF | | | | | −0.159 | −0.249 | −0.216 | −0.154 | −0.345 |
| | | | | | (0.083) | (0.080) | (0.078) | (0.154) | (0.081) |
| HXZ | | | | | | −0.090 | −0.057 | 0.005 | −0.186 |
| | | | | | | (0.393) | (0.507) | (0.958) | (0.259) |
| FF5 | | | | | | | 0.033 | 0.095 | −0.096 |
| | | | | | | | (0.196) | (0.514) | (0.466) |
| FF4 | | | | | | | | 0.062 | −0.129 |
| | | | | | | | | (0.636) | (0.324) |
| SY4 | | | | | | | | | −0.191 |
| | | | | | | | | | (0.275) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.080 | −0.301 | −0.106 | −0.077 | −0.140 | −0.212 | −0.158 | −0.174 | −0.352 |
| | (0.103) | (0.066) | (0.328) | (0.158) | (0.092) | (0.059) | (0.033) | (0.092) | (0.111) |
| FF3 | | −0.222 | −0.026 | 0.003 | −0.061 | −0.132 | −0.078 | −0.095 | −0.272 |
| | | (0.054) | (0.510) | (0.891) | (0.430) | (0.235) | (0.290) | (0.334) | (0.145) |
| FFC | | | 0.196 | 0.225 | 0.161 | 0.089 | 0.144 | 0.127 | −0.050 |
| | | | (0.352) | (0.245) | (0.410) | (0.658) | (0.468) | (0.449) | (0.432) |
| FFPS | | | | 0.029 | −0.035 | −0.106 | −0.052 | −0.068 | −0.246 |
| | | | | (0.700) | (0.777) | (0.452) | (0.658) | (0.556) | (0.227) |
| FFAF | | | | | −0.064 | −0.135 | −0.081 | −0.097 | −0.275 |
| | | | | | (0.491) | (0.241) | (0.350) | (0.342) | (0.142) |
| HXZ | | | | | | −0.072 | −0.017 | −0.034 | −0.211 |
| | | | | | | (0.471) | (0.814) | (0.738) | (0.239) |
| FF5 | | | | | | | 0.055 | 0.038 | −0.140 |
| | | | | | | | (0.185) | (0.779) | (0.431) |
| FF4 | | | | | | | | −0.017 | −0.194 |
| | | | | | | | | (0.890) | (0.273) |
| SY4 | | | | | | | | | −0.178 |
| | | | | | | | | | (0.276) |

Table 1.11: Tests of equality of cross-sectional $R^2$s: 30 IND portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 30 IND (industry) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.044 | −0.046 | −0.045 | −0.046 | −0.168 | −0.280 | −0.206 | −0.210 | −0.183 |
| | (0.782) | (0.936) | (0.941) | (0.773) | (0.644) | (0.645) | (0.635) | (0.550) | (0.907) |
| FF3 | | −0.001 | −0.001 | −0.001 | −0.123 | −0.235 | −0.162 | −0.166 | −0.139 |
| | | (0.927) | (0.953) | (0.949) | (0.615) | (0.427) | (0.636) | (0.526) | (0.645) |
| FFC | | | 0.001 | 0.000 | −0.122 | −0.234 | −0.161 | −0.164 | −0.138 |
| | | | (0.971) | (0.996) | (0.615) | (0.428) | (0.626) | (0.531) | (0.636) |
| FFPS | | | | −0.001 | −0.123 | −0.235 | −0.161 | −0.165 | 0.000 |
| | | | | (0.985) | (0.600) | (0.416) | (0.622) | (0.516) | (0.604) |
| FFAF | | | | | −0.122 | −0.234 | −0.161 | −0.164 | −0.138 |
| | | | | | (0.601) | (0.414) | (0.634) | (0.511) | (0.640) |
| HXZ | | | | | | −0.112 | −0.039 | −0.042 | −0.016 |
| | | | | | | (0.387) | (0.805) | (0.708) | (0.884) |
| FF5 | | | | | | | 0.073 | 0.070 | 0.096 |
| | | | | | | | (0.456) | (0.478) | (0.619) |
| FF4 | | | | | | | | −0.004 | 0.023 |
| | | | | | | | | (0.987) | (0.781) |
| SY4 | | | | | | | | | 0.027 |
| | | | | | | | | | (0.888) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.087 | −0.102 | −0.087 | −0.080 | −0.113 | −0.164 | −0.161 | −0.104 | −0.170 |
| | (0.381) | (0.520) | (0.591) | (0.404) | (0.498) | (0.518) | (0.361) | (0.562) | (0.671) |
| FF3 | | −0.015 | 0.000 | 0.007 | −0.027 | −0.077 | −0.074 | −0.017 | −0.083 |
| | | (0.574) | (0.967) | (0.769) | (0.711) | (0.525) | (0.549) | (0.845) | (0.564) |
| FFC | | | 0.015 | 0.022 | −0.012 | −0.062 | −0.059 | −0.002 | −0.068 |
| | | | (0.786) | (0.750) | (0.916) | (0.664) | (0.682) | (0.986) | (0.628) |
| FFPS | | | | 0.007 | −0.026 | −0.077 | −0.074 | −0.017 | −0.083 |
| | | | | (0.761) | (0.708) | (0.524) | (0.549) | (0.845) | (0.563) |
| FFAF | | | | | −0.033 | −0.084 | −0.081 | −0.024 | −0.090 |
| | | | | | (0.622) | (0.482) | (0.502) | (0.769) | (0.529) |
| HXZ | | | | | | −0.051 | −0.048 | 0.009 | −0.057 |
| | | | | | | (0.489) | (0.534) | (0.886) | (0.645) |
| FF5 | | | | | | | 0.003 | 0.060 | −0.006 |
| | | | | | | | (0.819) | (0.509) | (0.964) |
| FF4 | | | | | | | | 0.057 | −0.009 |
| | | | | | | | | (0.574) | (0.939) |
| SY4 | | | | | | | | | −0.066 |
| | | | | | | | | | (0.682) |

Table 1.12: Tests of equality of cross-sectional $R^2$s: 8 D10−1 portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on the 8 D10−1 (high minus low decile) portfolios. Panel A (Panel B) shows the difference between the OLS (GLS) cross-sectional regression $R^2$s of the factor models in row $i$ and column $j$, denoted $\hat{\rho}_i^2 - \hat{\rho}_j^2$, and the corresponding $p$-value (in parentheses) calculated using the Newey and West (1987)-adjusted $t$-statistic for the test of $H_0$: $\rho_i^2 = \rho_j^2$. The one-tailed (two-tailed) $p$-values in the cases of comparing nested (nonnested) models are computed under the assumption that the factor models are potentially misspecified. The sample period is from January 1968 to December 2016.

Panel A: OLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.690 | −0.861 | −0.832 | −0.543 | −0.889 | −0.914 | −0.817 | −0.972 | −0.986 |
| | (0.026) | (0.035) | (0.291) | (0.051) | (0.011) | (0.009) | (0.008) | (0.007) | (0.039) |
| FF3 | | −0.171 | −0.142 | 0.147 | −0.199 | −0.224 | −0.127 | −0.281 | −0.296 |
| | | (0.071) | (0.198) | (0.172) | (0.176) | (0.204) | (0.203) | (0.195) | (0.195) |
| FFC | | | 0.029 | 0.318 | −0.028 | −0.053 | 0.043 | −0.111 | −0.126 |
| | | | (0.877) | (0.192) | (0.817) | (0.733) | (0.798) | (0.324) | (0.267) |
| FFPS | | | | 0.289 | −0.057 | −0.082 | 0.014 | −0.140 | 0.017 |
| | | | | (0.246) | (0.740) | (0.690) | (0.940) | (0.500) | (0.482) |
| FFAF | | | | | −0.346 | −0.371 | −0.275 | −0.429 | −0.444 |
| | | | | | (0.121) | (0.099) | (0.125) | (0.112) | (0.111) |
| HXZ | | | | | | −0.025 | 0.071 | −0.083 | −0.098 |
| | | | | | | (0.837) | (0.412) | (0.554) | (0.518) |
| FF5 | | | | | | | 0.097 | −0.058 | −0.072 |
| | | | | | | | (0.155) | (0.580) | (0.528) |
| FF4 | | | | | | | | −0.154 | −0.169 |
| | | | | | | | | (0.389) | (0.381) |
| SY4 | | | | | | | | | −0.015 |
| | | | | | | | | | (0.642) |

Panel B: GLS

| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
|---|---|---|---|---|---|---|---|---|---|
| CAPM | −0.607 | −0.669 | −0.687 | −0.461 | −0.797 | −0.823 | −0.782 | −0.883 | −0.913 |
| | (0.005) | (0.010) | (0.111) | (0.016) | (0.001) | (0.002) | (0.001) | (0.000) | (0.014) |
| FF3 | | −0.062 | −0.080 | 0.146 | −0.191 | −0.216 | −0.175 | −0.276 | −0.306 |
| | | (0.310) | (0.389) | (0.181) | (0.186) | (0.268) | (0.216) | (0.197) | (0.187) |
| FFC | | | −0.018 | 0.207 | −0.129 | −0.154 | −0.114 | −0.214 | −0.244 |
| | | | (0.913) | (0.308) | (0.215) | (0.507) | (0.533) | (0.272) | (0.234) |
| FFPS | | | | 0.226 | −0.110 | −0.136 | −0.095 | −0.196 | −0.226 |
| | | | | (0.336) | (0.537) | (0.593) | (0.653) | (0.410) | (0.353) |
| FFAF | | | | | −0.336 | −0.361 | −0.321 | −0.422 | −0.452 |
| | | | | | (0.134) | (0.110) | (0.103) | (0.112) | (0.105) |
| HXZ | | | | | | −0.025 | 0.015 | −0.085 | −0.116 |
| | | | | | | (0.880) | (0.896) | (0.520) | (0.438) |
| FF5 | | | | | | | 0.040 | −0.060 | −0.090 |
| | | | | | | | (0.356) | (0.620) | (0.519) |
| FF4 | | | | | | | | −0.101 | −0.131 |
| | | | | | | | | (0.459) | (0.422) |
| SY4 | | | | | | | | | −0.030 |
| | | | | | | | | | (0.639) |

Table 1.13: Summary of factor model performance: Tests of equality of cross-sectional $R^2$s

The table reports summary of pairwise tests for equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. The test assets are the value-weighted monthly excess returns on anomaly portfolios: the 25 size-STR (short-term reversal) portfolios, the 25 size-CI (abnormal capital investment) portfolios, the 25 size-DR (distress risk) portfolios, the 25 size-$\beta$ (market beta) portfolios, the 35 size-NI (net share issues) portfolios, the 25 size-MAX (lottery demand) portfolios, the 25 size-RVar (residual variance) portfolios, the 25 size-AC (accruals) portfolios, the 30 IND (industry) portfolios, and the 8 D10−1 (high minus low decile) portfolios. Panel A (Panel B) shows, for each set of anomaly portfolios, the number of times a given factor model produces a significantly (i.e., at the 5% level) higher OLS (GLS) cross-sectional regression $R^2$ relative to another competing factor model. See also notes to Table 1.3.

| Panel A: OLS | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Size-STR | Size-CI | Size-DR | Size-$\beta$ | Size-NI | Size-MAX | Size-RVar | Size-AC | IND | D10−1 |
| CAPM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| FF3 | 1 | 1 | 0 | 0 | 2 | 1 | 1 | 0 | 0 | 1 |
| FFC | 0 | 1 | 0 | 0 | 2 | 1 | 2 | 1 | 0 | 1 |
| FFPS | 0 | 1 | 0 | 0 | 2 | 1 | 2 | 0 | 0 | 0 |
| FFAF | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| HXZ | 0 | 1 | 0 | 1 | 3 | 1 | 3 | 0 | 0 | 1 |
| FF5 | 0 | 1 | 0 | 1 | 3 | 0 | 4 | 1 | 0 | 1 |
| FF4 | 1 | 1 | 0 | 1 | 3 | 1 | 4 | 1 | 0 | 1 |
| SY4 | 0 | 0 | 0 | 1 | 4 | 1 | 2 | 0 | 0 | 1 |
| BS6 | 1 | 0 | 0 | 0 | 3 | 2 | 3 | 0 | 0 | 1 |
| Panel B: GLS | | | | | | | | | | |
| CAPM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| FF3 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| FFC | 1 | 2 | 0 | 1 | 2 | 1 | 0 | 0 | 0 | 1 |
| FFPS | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| FFAF | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| HXZ | 0 | 1 | 0 | 1 | 4 | 2 | 2 | 0 | 0 | 1 |
| FF5 | 0 | 1 | 0 | 1 | 2 | 1 | 6 | 0 | 0 | 1 |
| FF4 | 1 | 1 | 0 | 1 | 2 | 2 | 6 | 1 | 0 | 1 |
| SY4 | 0 | 2 | 0 | 1 | 4 | 2 | 1 | 0 | 0 | 1 |
| BS6 | 1 | 1 | 0 | 0 | 2 | 1 | 5 | 0 | 0 | 1 |

## Table 1.14: Multiple model comparison tests

The table reports multiple model comparison tests of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. $\hat{\rho}^2$ is the cross-sectional regression $R^2$ of the benchmark model; $u$ is the number of alternative factor models in each multiple nonnested model comparison; LR is the value of the likelihood ratio statistic with corresponding $p$-value reported in adjacent column; $v$ is the number of factor models that nest the benchmark model; $\hat{\rho}^2_M - \hat{\rho}^2$ is the difference between the cross-sectional regression $R^2$ of the expanded factor model ($M$) and the cross-sectional regression $R^2$ of the benchmark model with corresponding $p$-value reported in adjacent column. The sample period is from January 1968 to December 2016. See also notes to Table 1.13.

Panel A: 25 size-STR portfolios

| Benchmark | OLS | | | | | | | GLS | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.216 | | | | 9 | 0.744 | 0.440 | 0.008 | | | | 9 | 0.734 | 0.749 |
| FF3 | 0.793 | 5 | 1.281 | 0.463 | 2 | 0.048 | 0.438 | 0.221 | 5 | 2.448 | 0.283 | 2 | 0.110 | 0.267 |
| FFC | 0.798 | 6 | 1.274 | 0.601 | | | | 0.229 | 6 | 2.875 | 0.309 | | | |
| FFPS | 0.838 | 6 | 0.196 | 0.650 | | | | 0.312 | 6 | 0.780 | 0.433 | | | |
| FFAF | 0.703 | 6 | 3.245 | 0.140 | | | | 0.201 | 6 | 3.891 | 0.164 | | | |
| HXZ | 0.726 | 6 | 0.861 | 0.298 | | | | 0.123 | 6 | 4.007 | 0.087 | | | |
| FF5 | 0.843 | 6 | 0.663 | 0.716 | | | | 0.285 | 6 | 2.736 | 0.245 | | | |
| FF4 | 0.788 | 6 | 0.636 | 0.559 | 1 | 0.055 | 0.295 | 0.198 | 6 | 3.993 | 0.143 | 1 | 0.087 | 0.143 |
| SY4 | 0.769 | 6 | 1.598 | 0.402 | | | | 0.171 | 6 | 3.106 | 0.180 | | | |
| BS6 | 0.876 | 6 | 0.000 | 0.858 | | | | 0.482 | 6 | 0.000 | 0.757 | | | |

Panel B: 25 size-CI portfolios

| Benchmark | OLS | | | | | | | GLS | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.341 | | | | 9 | 0.615 | 0.328 | 0.000 | | | | 9 | 0.832 | 0.291 |
| FF3 | 0.693 | 5 | 1.144 | 0.500 | 2 | 0.133 | 0.070 | 0.274 | 5 | 2.242 | 0.288 | 2 | 0.251 | 0.057 |
| FFC | 0.823 | 6 | 0.009 | 0.808 | | | | 0.507 | 6 | 0.000 | 0.841 | | | |
| FFPS | 0.706 | 6 | 1.017 | 0.494 | | | | 0.300 | 6 | 1.622 | 0.333 | | | |
| FFAF | 0.642 | 6 | 1.577 | 0.224 | | | | 0.128 | 6 | 7.392 | 0.020 | | | |
| HXZ | 0.744 | 6 | 0.819 | 0.515 | | | | 0.384 | 6 | 0.689 | 0.514 | | | |
| FF5 | 0.694 | 6 | 1.320 | 0.520 | | | | 0.297 | 6 | 2.408 | 0.282 | | | |
| FF4 | 0.693 | 6 | 1.381 | 0.500 | 1 | 0.001 | 0.831 | 0.287 | 6 | 2.838 | 0.230 | 1 | 0.010 | 0.604 |
| SY4 | 0.783 | 6 | 0.487 | 0.652 | | | | 0.467 | 6 | 0.130 | 0.733 | | | |
| BS6 | 0.827 | 6 | 0.000 | 0.812 | | | | 0.475 | 6 | 0.301 | 0.681 | | | |

*(Continued)*

Table 1.14 – *Continued*

| Panel C: 25 size-DR portfolios | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.522 | | | | 9 | 0.395 | 0.961 | 0.238 | | | | 9 | 0.399 | 0.992 |
| FF3 | 0.738 | 5 | 0.398 | 0.525 | 2 | 0.101 | 0.459 | 0.324 | 5 | 1.048 | 0.454 | 2 | 0.173 | 0.363 |
| FFC | 0.819 | 6 | 0.002 | 0.801 | | | | 0.480 | 6 | 0.053 | 0.784 | | | |
| FFPS | 0.741 | 6 | 0.309 | 0.546 | | | | 0.326 | 6 | 0.785 | 0.498 | | | |
| FFAF | 0.772 | 6 | 0.252 | 0.824 | | | | 0.371 | 6 | 0.458 | 0.722 | | | |
| HXZ | 0.768 | 6 | 0.357 | 0.602 | | | | 0.386 | 6 | 0.372 | 0.607 | | | |
| FF5 | 0.774 | 6 | 0.116 | 0.663 | | | | 0.341 | 6 | 0.537 | 0.576 | | | |
| FF4 | 0.709 | 6 | 0.575 | 0.473 | 1 | 0.065 | 0.232 | 0.297 | 6 | 1.478 | 0.370 | 1 | 0.044 | 0.404 |
| SY4 | 0.792 | 6 | 0.114 | 0.829 | | | | 0.388 | 6 | 0.411 | 0.652 | | | |
| BS6 | 0.820 | 6 | 0.000 | 0.896 | | | | 0.495 | 6 | 0.000 | 0.762 | | | |
| Panel D: 25 size-$\beta$ portfolios | | | | | | | | | | | | | | |
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.046 | | | | 9 | 0.856 | 0.226 | 0.001 | | | | 9 | 0.651 | 0.559 |
| FF3 | 0.739 | 5 | 0.825 | 0.548 | 2 | 0.093 | 0.108 | 0.218 | 5 | 2.043 | 0.261 | 2 | 0.233 | 0.082 |
| FFC | 0.830 | 6 | 0.000 | 0.868 | | | | 0.444 | 6 | 0.003 | 0.803 | | | |
| FFPS | 0.755 | 6 | 0.796 | 0.596 | | | | 0.246 | 6 | 1.435 | 0.362 | | | |
| FFAF | 0.600 | 6 | 1.888 | 0.157 | | | | 0.071 | 6 | 7.298 | 0.023 | | | |
| HXZ | 0.789 | 6 | 0.327 | 0.695 | | | | 0.337 | 6 | 0.681 | 0.603 | | | |
| FF5 | 0.795 | 6 | 0.259 | 0.838 | | | | 0.325 | 6 | 0.683 | 0.607 | | | |
| FF4 | 0.790 | 6 | 0.305 | 0.810 | 1 | 0.004 | 0.594 | 0.323 | 6 | 0.756 | 0.586 | 1 | 0.002 | 0.784 |
| SY4 | 0.796 | 6 | 0.155 | 0.667 | | | | 0.430 | 6 | 0.011 | 0.781 | | | |
| BS6 | 0.823 | 6 | 0.029 | 0.834 | | | | 0.448 | 6 | 0.000 | 0.857 | | | |
| Panel E: 35 size-NI portfolios | | | | | | | | | | | | | | |
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}_M^2 - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.081 | | | | 9 | 0.798 | 0.028 | 0.014 | | | | 9 | 0.589 | 0.051 |
| FF3 | 0.520 | 5 | 7.043 | 0.023 | 2 | 0.209 | 0.023 | 0.107 | 5 | 7.819 | 0.017 | 2 | 0.184 | 0.070 |
| FFC | 0.722 | 6 | 0.151 | 0.659 | | | | 0.292 | 6 | 0.462 | 0.489 | | | |
| FFPS | 0.545 | 6 | 4.396 | 0.079 | | | | 0.115 | 6 | 6.259 | 0.039 | | | |
| FFAF | 0.396 | 6 | 13.180 | 0.001 | | | | 0.043 | 6 | 13.793 | 0.001 | | | |
| HXZ | 0.726 | 6 | 0.154 | 0.792 | | | | 0.321 | 6 | 0.165 | 0.772 | | | |
| FF5 | 0.688 | 6 | 0.870 | 0.523 | | | | 0.240 | 6 | 2.511 | 0.229 | | | |
| FF4 | 0.678 | 6 | 0.829 | 0.488 | 1 | 0.011 | 0.412 | 0.237 | 6 | 2.326 | 0.244 | 1 | 0.003 | 0.681 |
| SY4 | 0.741 | 6 | 0.010 | 0.862 | | | | 0.350 | 6 | 0.000 | 0.863 | | | |
| BS6 | 0.746 | 6 | 0.000 | 0.899 | | | | 0.342 | 6 | 0.007 | 0.858 | | | |

*(Continued)*

Table 1.14 – *Continued*

| Panel F: 25 size-MAX portfolios | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.309 | | | | 9 | 0.636 | 0.763 | 0.000 | | | | 9 | 0.808 | 0.612 |
| FF3 | 0.623 | 5 | 1.509 | 0.409 | 2 | 0.111 | 0.138 | 0.107 | 5 | 4.866 | 0.060 | 2 | 0.134 | 0.215 |
| FFC | 0.692 | 6 | 0.046 | 0.810 | | | | 0.220 | 6 | 0.632 | 0.435 | | | |
| FFPS | 0.625 | 6 | 1.599 | 0.426 | | | | 0.110 | 6 | 4.583 | 0.085 | | | |
| FFAF | 0.522 | 6 | 4.390 | 0.060 | | | | 0.024 | 6 | 11.365 | 0.003 | | | |
| HXZ | 0.655 | 6 | 0.824 | 0.545 | | | | 0.229 | 6 | 1.149 | 0.500 | | | |
| FF5 | 0.675 | 6 | 0.195 | 0.636 | | | | 0.245 | 6 | 0.281 | 0.675 | | | |
| FF4 | 0.664 | 6 | 0.543 | 0.598 | 1 | 0.011 | 0.544 | 0.238 | 6 | 0.318 | 0.656 | 1 | 0.007 | 0.681 |
| SY4 | 0.668 | 6 | 0.433 | 0.679 | | | | 0.293 | 6 | 0.000 | 0.837 | | | |
| BS6 | 0.703 | 6 | 0.000 | 0.862 | | | | 0.263 | 6 | 0.107 | 0.832 | | | |
| Panel G: 25 size-RVar portfolios | | | | | | | | | | | | | | |
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.293 | | | | 9 | 0.671 | 0.282 | 0.000 | | | | 9 | 0.754 | 0.302 |
| FF3 | 0.589 | 5 | 6.676 | 0.020 | 2 | 0.188 | 0.066 | 0.028 | 5 | 12.002 | 0.002 | 2 | 0.041 | 0.576 |
| FFC | 0.774 | 6 | 1.766 | 0.316 | | | | 0.051 | 6 | 9.876 | 0.008 | | | |
| FFPS | 0.607 | 6 | 5.467 | 0.039 | | | | 0.031 | 6 | 11.818 | 0.003 | | | |
| FFAF | 0.389 | 6 | 10.582 | 0.002 | | | | 0.007 | 6 | 17.716 | 0.000 | | | |
| HXZ | 0.835 | 6 | 0.964 | 0.609 | | | | 0.266 | 6 | 2.812 | 0.206 | | | |
| FF5 | 0.874 | 6 | 0.000 | 0.858 | | | | 0.450 | 6 | 0.000 | 0.821 | | | |
| FF4 | 0.873 | 6 | 0.000 | 0.868 | 1 | 0.001 | 0.863 | 0.450 | 6 | 0.000 | 0.827 | 1 | 0.001 | 0.878 |
| SY4 | 0.813 | 6 | 1.399 | 0.490 | | | | 0.171 | 6 | 5.890 | 0.039 | | | |
| BS6 | 0.872 | 6 | 0.002 | 0.895 | | | | 0.392 | 6 | 0.364 | 0.545 | | | |
| Panel H: 25 size-AC portfolios | | | | | | | | | | | | | | |
| Benchmark | OLS | | | | | | | GLS | | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.041 | | | | 9 | 0.864 | 0.529 | 0.041 | | | | 9 | 0.707 | 0.899 |
| FF3 | 0.401 | 5 | 3.176 | 0.203 | 2 | 0.303 | 0.039 | 0.121 | 5 | 3.241 | 0.236 | 2 | 0.268 | 0.118 |
| FFC | 0.679 | 6 | 0.558 | 0.497 | | | | 0.343 | 6 | 0.641 | 0.452 | | | |
| FFPS | 0.422 | 6 | 2.304 | 0.234 | | | | 0.147 | 6 | 1.724 | 0.296 | | | |
| FFAF | 0.376 | 6 | 3.007 | 0.158 | | | | 0.118 | 6 | 3.315 | 0.209 | | | |
| HXZ | 0.535 | 6 | 1.350 | 0.463 | | | | 0.182 | 6 | 1.720 | 0.355 | | | |
| FF5 | 0.625 | 6 | 0.496 | 0.605 | | | | 0.253 | 6 | 0.643 | 0.508 | | | |
| FF4 | 0.592 | 6 | 0.856 | 0.554 | 1 | 0.033 | 0.196 | 0.199 | 6 | 1.304 | 0.409 | 1 | 0.055 | 0.185 |
| SY4 | 0.530 | 6 | 1.292 | 0.403 | | | | 0.215 | 6 | 1.352 | 0.421 | | | |
| BS6 | 0.721 | 6 | 0.000 | 0.865 | | | | 0.393 | 6 | 0.000 | 0.866 | | | |

*(Continued)*

Table 14 – *Continued*

| Panel I: 30 IND portfolios | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Benchmark | OLS | | | | | | | GLS | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.084 | | | | 9 | 0.561 | 0.968 | 0.008 | | | | 9 | 0.357 | 0.984 |
| FF3 | 0.128 | 5 | 1.019 | 0.328 | 2 | 0.002 | 0.993 | 0.094 | 5 | 0.527 | 0.567 | 2 | 0.016 | 0.841 |
| FFC | 0.130 | 6 | 1.013 | 0.401 | | | | 0.109 | 6 | 0.277 | 0.584 | | | |
| FFPS | 0.129 | 6 | 1.169 | 0.563 | | | | 0.094 | 6 | 0.681 | 0.701 | | | |
| FFAF | 0.130 | 6 | 1.106 | 0.403 | | | | 0.087 | 6 | 0.800 | 0.624 | | | |
| HXZ | 0.251 | 6 | 1.287 | 0.519 | | | | 0.121 | 6 | 0.659 | 0.690 | | | |
| FF5 | 0.364 | 6 | 0.000 | 0.834 | | | | 0.172 | 6 | 0.002 | 0.807 | | | |
| FF4 | 0.290 | 6 | 0.000 | 0.737 | 1 | 0.073 | 0.456 | 0.169 | 6 | 0.006 | 0.801 | 1 | 0.003 | 0.819 |
| SY4 | 0.294 | 6 | 0.609 | 0.544 | | | | 0.111 | 6 | 0.468 | 0.545 | | | |
| BS6 | 0.267 | 6 | 0.269 | 0.515 | | | | 0.177 | 6 | 0.000 | 0.719 | | | |
| Panel J: 8 D10−1 portfolios | | | | | | | | | | | | | |
| Benchmark | OLS | | | | | | | GLS | | | | | |
| | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value | $\hat{\rho}^2$ | $u$ | LR | $p$-value | $v$ | $\hat{\rho}^2_M - \hat{\rho}^2$ | $p$-value |
| CAPM | 0.004 | | | | 9 | – | – | 0.067 | | | | 9 | – | – |
| FF3 | 0.694 | 5 | 2.243 | 0.224 | 2 | 0.177 | 0.322 | 0.674 | 5 | 2.706 | 0.186 | 2 | 0.084 | 0.704 |
| FFC | 0.865 | 6 | 1.178 | 0.441 | | | | 0.736 | 6 | 2.144 | 0.265 | | | |
| FFPS | 0.836 | 6 | 0.500 | 0.480 | | | | 0.754 | 6 | 0.941 | 0.370 | | | |
| FFAF | 0.547 | 6 | 4.399 | 0.056 | | | | 0.528 | 6 | 5.055 | 0.048 | | | |
| HXZ | 0.893 | 6 | 0.362 | 0.730 | | | | 0.865 | 6 | 0.616 | 0.694 | | | |
| FF5 | 0.918 | 6 | 0.369 | 0.675 | | | | 0.890 | 6 | 0.429 | 0.580 | | | |
| FF4 | 0.822 | 6 | 0.769 | 0.562 | 1 | 0.097 | 0.155 | 0.849 | 6 | 0.672 | 0.578 | 1 | 0.040 | 0.356 |
| SY4 | 0.976 | 6 | 0.202 | 0.813 | | | | 0.950 | 6 | 0.218 | 0.783 | | | |
| BS6 | 0.991 | 6 | 0.000 | 0.858 | | | | 0.980 | 6 | 0.000 | 0.860 | | | |

Table 1.15: Summary of factor model performance: Multiple model comparison tests

The table reports summary of multiple model comparison tests of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. For each set of anomaly portfolios, X (✓) denotes a rejection of the null hypothesis, at the 5% level, that the benchmark model given in column 1 performs at least as well as all other competing nested (nonnested) factor models. See also notes to Tables 1.13 and 1.14.

| Panel A: OLS | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Size-STR | Size-CI | Size-DR | Size-$\beta$ | Size-NI | Size-MAX | Size-RVar | Size-AC | IND | D10−1 |
| CAPM | | | | | X | | | | | |
| FF3 | | | | | X ✓ | | ✓ | X | | |
| FFC | | | | | | | | | | |
| FFPS | | | | | | | ✓ | | | |
| FFAF | | | | | ✓ | | ✓ | | | |
| HXZ | | | | | | | | | | |
| FF5 | | | | | | | | | | |
| FF4 | | | | | | | | | | |
| SY4 | | | | | | | | | | |
| BS6 | | | | | | | | | | |
| **Panel B: GLS** | | | | | | | | | | |
| CAPM | | | | | | | | | | |
| FF3 | | | | | ✓ | | ✓ | | | |
| FFC | | | | | | | ✓ | | | |
| FFPS | | | | | ✓ | | ✓ | | | |
| FFAF | | ✓ | | ✓ | ✓ | ✓ | ✓ | | | ✓ |
| HXZ | | | | | | | | | | |
| FF5 | | | | | | | | | | |
| FF4 | | | | | | | | | | |
| SY4 | | | | | | | ✓ | | | |
| BS6 | | | | | | | | | | |

# Appendix

This Appendix describes the construction of test asset portfolios, which are not available in the Data Library maintained by Kenneth R. French. I obtain daily and monthly stock return data from the Center for Research in Security Prices (CRSP) and a host of firm-specific accounting information from the Compustat Annual Industrial Files. The sample for constructing anomaly portfolios includes all NYSE-, AMEX-, and NASDAQ-listed ordinary common stocks (CRSP share codes 10 and 11).[14] In line with Fama and French (1992), I employ all accounting variables at the end of June of calendar year $t$ by using accounting information available for the fiscal year ending in the calendar year $t-1$ from Compustat. Finally, this Appendix also describes the sequential test for comparing nonnested models and provides additional results on the factor model time-series and cross-sectional regressions.

## 25 size-CI and D10−1 CI portfolios:

In line with Titman, Wei, and Xie (2004), I first estimate abnormal capital investment (CI) at the end of June of year $t$ as $\text{CE}_{t-1}/[(\text{CE}_{t-2} + \text{CE}_{t-3} + \text{CE}_{t-4})/3] - 1$, where $\text{CE}_{t-j}$ is capital expenditure (Compustat item CAPX) scaled by sales (Compustat item SALE) for the fiscal year ending in calendar year $t$-$j$. I then construct 25 value-weighted portfolios at the end of June of each year $t$ from independent sorts of stocks into quintiles of size and CI. The size quintiles are based on NYSE market equity breakpoints at the end of June of year $t$. The CI quintile breakpoints are also based on NYSE stocks. I compute monthly portfolio returns from July of year $t$ to June of year $t+1$ and rebalance portfolios at the end of June of year $t+1$.

At the end of June of each year $t$, I also use NYSE breakpoints to assign stocks into deciles based on CI. Then value-weighted monthly decile returns are computed from July of year $t$ to June of year $t+1$ and the deciles are rebalanced at the end of June of year $t+1$. Decile 1 contains stocks with the lowest CI and decile 10 contains stocks with the highest CI. The return difference between decile 10 and decile 1 is the D10−1 (high minus low decile) CI portfolio.

## 25 size-DR and D10−1 DR portfolios:

To proxy for distress risk (DR), I use the Bharath and Shumway (2008) measure of expected default frequency (EDF), which is a simplified version of the distance to default

[14] To compute excess returns on independent two-way sorted portfolios, I subtract monthly risk-free security return taken from Kenneth R. French's website.

(DD) measure introduced by Merton (1974). The EDF of firm $i$ is estimated as follows:

$$\mathrm{DD}_{i,t} = \frac{\log\left(\frac{\mathrm{Equity}_{i,t} + \mathrm{Debt}_{i,t}}{\mathrm{Debt}_{i,t}}\right) + \left(r_{i,t-1} - \frac{\sigma_{Vi,t}^2}{2}\right) \times T_{i,t}}{\sigma_{Vi,t} \times \sqrt{T_{i,t}}}, \tag{1.A1}$$

$$\sigma_{Vi,t} = \frac{\mathrm{Equity}_{i,t}}{\mathrm{Equity}_{i,t} + \mathrm{Debt}_{i,t}} \times \sigma_{Ei,t} + \frac{\mathrm{Equity}_{i,t}}{\mathrm{Equity}_{i,t} + \mathrm{Debt}_{i,t}} \times (0.05 + 0.25 \times \sigma_{Ei,t}), \tag{1.A2}$$

and

$$\mathrm{EDF}_{i,t} = N(-\mathrm{DD}_{i,t}), \tag{1.A3}$$

where $\mathrm{Equity}_{i,t}$ is the market value of equity (in millions of dollars) calculated as the number of shares outstanding times the (absolute) price of the stock at the end of June of year $t$; $\mathrm{Debt}_{i,t}$ is the face value of debt computed as the sum of debt in current liabilities (Compustat item DLC) and one-half of long-term debt (Compustat item DLTT) at the end of June of year $t$; $r_{i,t-1}$ is the past 12-month cumulative return; $\sigma_{Ei,t}$ is the stock return volatility estimated using the monthly stock return from the past 12-month; $\sigma_{Vi,t}$, calculated from $\sigma_{Ei,t}$, is an approximation of the volatility of assets; and $N(.)$ is the cumulative standard normal distribution function. I set $T_{i,t}$ to one year and construct $\mathrm{DD}_{i,t}$ of all sample firms at the end of June of each year.

The 25 value-weighted size-DR portfolios are constructed in the same way as the 25 value-weighted size-CI portfolios, except the second sort is on EDF, which I estimate as above to proxy for DR. Analogous to D10−1 CI portfolio, I construct D10−1 DR portfolio as the return difference between EDF decile 10 (high EDF) and EDF decile 1 (low EDF).

## 25 size-MAX and D10−1 MAX portfolios:

Consistent with Bali, Cakici, and Whitelaw (2011), I compute lottery demand at the beginning of each month using MAX, defined as the maximum daily return within the previous month. Then the 25 value-weighted size-MAX portfolios are constructed from independent sorts of stocks into quintiles of size and MAX. The monthly size quintile and MAX quintile breakpoints are based on NYSE stocks. I compute portfolio returns for the current month and rebalance portfolios at the beginning of the following month.

At the beginning of each month, I use NYSE breakpoints to sort stocks into deciles based on their MAX. Monthly decile returns are computed for the current month and the deciles are rebalanced at the beginning of the next month. The D10−1 MAX portfolio is then constructed as the return difference between MAX decile 10 (high MAX) and MAX decile 1 (low MAX).

## Sequential test:

The testing of $H_0$: $\rho_A^2 = \rho_B^2$ for nonnested models entails a sequential procedure (see Kan, Robotti, and Shanken (2013) and Vuong (1989)). First, I test $H_0$: $y_A = y_B$, where $y_A$ and $y_B$ are the normalized stochastic discount factors for models $A$ and $B$, respectively. If I reject $H_0$: $y_A = y_B$ at the 5% level of significance, then I proceed to test $H_0$: $\rho_A^2 = \rho_B^2 = 1$. Finally, if I still reject $H_0$: $\rho_A^2 = \rho_B^2 = 1$ at the 5% significance level, then I perform the normal test of $H_0$: $0 < \rho_A^2 = \rho_B^2 < 1$.

Table 1.A1: Factor correlations

The table reports factor correlations. MKT, SMB* (small minus big), and HML (high minus low) are, respectively, the market, size, and value factors of Fama and French (1993); LIQ is the traded liquidity factor of Pástor and Stambaugh (2003); $\text{HML}^m$ is the value factor of Asness and Frazzini (2013); $r_{\text{ME}}$, $r_{\text{I/A}}$, and $r_{\text{ROE}}$ are, respectively, the size, investment, and profitability factors of Hou, Xue, and Zhang (2015); SMB, RMW (robust minus weak), CMA (conservative minus aggressive), and UMD (up minus down) are, respectively, the size, profitability, investment, and momentum factors of Fama and French (2015, 2016); and $\text{SMB}_M$, MGMT, and PERF are the size and two mispricing factors of Stambaugh and Yuan (2016), respectively. The sample period is from January 1968 to December 2016.

| | SMB* | HML | SMB | RMW | CMA | UMD | LIQ | $\text{HML}^m$ | $\text{SMB}_M$ | MGMT | PERF | $r_{\text{ME}}$ | $r_{\text{I/A}}$ | $r_{\text{ROE}}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MKT | 0.290 | −0.274 | 0.269 | −0.240 | −0.397 | −0.141 | −0.012 | −0.122 | 0.255 | −0.542 | −0.265 | 0.262 | −0.381 | −0.203 |
| SMB* | | −0.210 | 0.985 | −0.428 | −0.146 | −0.023 | −0.002 | −0.105 | 0.922 | −0.404 | −0.132 | 0.952 | −0.250 | −0.384 |
| HML | | | −0.087 | 0.098 | 0.698 | −0.185 | 0.032 | 0.778 | −0.056 | 0.708 | −0.307 | −0.044 | 0.676 | −0.133 |
| SMB | | | | −0.372 | −0.078 | −0.050 | −0.007 | −0.006 | 0.942 | −0.331 | −0.156 | 0.974 | −0.178 | −0.382 |
| RMW | | | | | −0.007 | 0.108 | 0.002 | −0.049 | −0.290 | 0.232 | 0.438 | −0.375 | 0.106 | 0.669 |
| CMA | | | | | | 0.007 | 0.003 | 0.511 | −0.054 | 0.781 | −0.056 | −0.044 | 0.909 | −0.081 |
| UMD | | | | | | | −0.013 | −0.648 | 0.004 | 0.046 | 0.721 | −0.021 | 0.029 | 0.503 |
| LIQ | | | | | | | | 0.074 | 0.006 | −0.006 | 0.027 | −0.015 | 0.009 | −0.082 |
| $\text{HML}^m$ | | | | | | | | | −0.029 | 0.489 | −0.633 | 0.001 | 0.494 | −0.453 |
| $\text{SMB}_M$ | | | | | | | | | | −0.280 | −0.093 | 0.926 | −0.139 | −0.292 |
| MGMT | | | | | | | | | | | 0.018 | −0.299 | 0.771 | 0.086 |
| PERF | | | | | | | | | | | | −0.152 | −0.049 | 0.644 |
| $r_{\text{ME}}$ | | | | | | | | | | | | | −0.141 | −0.320 |
| $r_{\text{I/A}}$ | | | | | | | | | | | | | | 0.048 |

Table 1.A2: Average excess returns and alphas of the 25 size-STR portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-STR (short-term reversal) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.99 | 0.68 | 0.65 | 0.59 | −0.03 | 2.85 | 2.27 | 2.28 | 2.05 | −0.09 |
| 2 | 1.01 | 0.98 | 0.76 | 0.58 | 0.29 | 3.07 | 3.71 | 3.03 | 2.38 | 1.02 |
| 3 | 0.92 | 0.85 | 0.78 | 0.59 | 0.29 | 3.04 | 3.51 | 3.29 | 2.61 | 1.12 |
| 4 | 0.80 | 0.94 | 0.70 | 0.53 | 0.27 | 2.74 | 3.92 | 3.31 | 2.52 | 1.12 |
| Big | 0.53 | 0.59 | 0.50 | 0.45 | 0.27 | 2.15 | 2.78 | 2.68 | 2.31 | 1.30 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.29 | 0.12 | 0.15 | 0.10 | −0.60 | 1.49 | 0.74 | 0.90 | 0.59 | −3.18 |
| 2 | 0.28 | 0.40 | 0.23 | 0.05 | −0.31 | 1.74 | 3.20 | 1.83 | 0.41 | −2.25 |
| 3 | 0.22 | 0.29 | 0.25 | 0.08 | −0.27 | 1.53 | 2.64 | 2.55 | 0.92 | −2.15 |
| 4 | 0.12 | 0.38 | 0.20 | 0.04 | −0.27 | 0.85 | 3.84 | 2.42 | 0.55 | −2.75 |
| Big | −0.05 | 0.11 | 0.05 | 0.01 | −0.20 | −0.41 | 1.46 | 0.84 | 0.11 | −2.10 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | 0.07 | −0.14 | −0.11 | −0.15 | −0.75 | 0.56 | −1.58 | −1.17 | −1.61 | −6.62 |
| 2 | 0.14 | 0.20 | 0.02 | −0.12 | −0.38 | 1.24 | 2.80 | 0.33 | −1.90 | −4.26 |
| 3 | 0.14 | 0.13 | 0.08 | −0.04 | −0.31 | 1.11 | 1.68 | 1.14 | −0.70 | −3.17 |
| 4 | 0.07 | 0.25 | 0.08 | −0.05 | −0.27 | 0.49 | 3.15 | 1.29 | −0.70 | −2.99 |
| Big | −0.07 | 0.09 | 0.06 | 0.02 | −0.14 | −0.51 | 1.29 | 1.20 | 0.31 | −1.53 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.40 | −0.01 | 0.01 | −0.07 | −0.68 | 2.92 | −0.13 | 0.06 | −0.74 | −5.28 |
| 2 | 0.35 | 0.29 | 0.07 | −0.08 | −0.37 | 3.17 | 4.29 | 1.21 | −1.14 | −3.76 |
| 3 | 0.33 | 0.21 | 0.11 | −0.03 | −0.34 | 2.76 | 2.91 | 1.66 | −0.43 | −3.27 |
| 4 | 0.24 | 0.33 | 0.11 | −0.04 | −0.27 | 1.80 | 4.11 | 1.61 | −0.47 | −2.69 |
| Big | 0.07 | 0.10 | 0.04 | 0.01 | −0.22 | 0.45 | 1.26 | 0.68 | 0.17 | −2.28 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | 0.06 | −0.13 | −0.10 | −0.14 | −0.76 | 0.52 | −1.50 | −1.09 | −1.51 | −6.75 |
| 2 | 0.14 | 0.20 | 0.03 | −0.12 | −0.37 | 1.21 | 2.85 | 0.42 | −1.78 | −4.10 |
| 3 | 0.12 | 0.12 | 0.07 | −0.04 | −0.29 | 0.95 | 1.69 | 1.06 | −0.70 | −3.06 |
| 4 | 0.03 | 0.23 | 0.07 | −0.05 | −0.30 | 0.21 | 3.03 | 1.11 | −0.71 | −3.32 |
| Big | −0.09 | 0.07 | 0.07 | 0.02 | −0.13 | −0.66 | 1.00 | 1.32 | 0.33 | −1.41 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | 0.00 | −0.09 | −0.05 | −0.08 | −0.73 | 0.04 | −1.17 | −0.55 | −0.84 | −6.43 |
| 2 | 0.09 | 0.24 | 0.08 | −0.07 | −0.37 | 0.89 | 3.66 | 1.23 | −1.13 | −4.21 |
| 3 | 0.08 | 0.16 | 0.13 | 0.00 | −0.29 | 0.72 | 2.23 | 1.97 | 0.04 | −3.12 |
| 4 | 0.00 | 0.27 | 0.12 | −0.01 | −0.27 | 0.01 | 3.55 | 1.78 | −0.10 | −3.07 |
| Big | −0.12 | 0.10 | 0.07 | 0.03 | −0.13 | −1.00 | 1.36 | 1.46 | 0.46 | −1.47 |

*(Continued)*

Table 1.A3 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.58 | 0.01 | 0.00 | −0.07 | −0.53 | 2.49 | 0.09 | −0.01 | −0.58 | −4.05 |
| 2 | 0.45 | 0.24 | 0.03 | −0.09 | −0.28 | 2.58 | 2.19 | 0.34 | −1.16 | −2.41 |
| 3 | 0.42 | 0.11 | 0.03 | −0.06 | −0.22 | 2.67 | 1.15 | 0.38 | −0.79 | −1.68 |
| 4 | 0.35 | 0.26 | 0.00 | −0.11 | −0.18 | 2.03 | 2.71 | 0.00 | −1.29 | −1.56 |
| Big | 0.12 | 0.08 | −0.04 | −0.02 | −0.13 | 0.70 | 0.99 | −0.71 | −0.22 | −1.20 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.30 | −0.10 | −0.12 | −0.15 | −0.65 | 1.67 | −1.06 | −1.24 | −1.60 | −5.69 |
| 2 | 0.33 | 0.20 | −0.01 | −0.14 | −0.31 | 2.21 | 2.43 | −0.13 | −2.27 | −3.26 |
| 3 | 0.31 | 0.08 | 0.03 | −0.07 | −0.23 | 2.07 | 1.02 | 0.51 | −1.08 | −2.20 |
| 4 | 0.23 | 0.22 | −0.01 | −0.10 | −0.21 | 1.44 | 2.73 | −0.09 | −1.41 | −2.20 |
| Big | 0.03 | 0.08 | 0.01 | −0.01 | −0.09 | 0.21 | 1.22 | 0.11 | −0.11 | −0.94 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.29 | −0.11 | −0.13 | −0.16 | −0.65 | 1.55 | −1.03 | −1.19 | −1.54 | −5.74 |
| 2 | 0.32 | 0.19 | −0.01 | −0.15 | −0.30 | 2.07 | 2.09 | −0.22 | −2.19 | −3.05 |
| 3 | 0.30 | 0.07 | 0.02 | −0.07 | −0.23 | 2.00 | 0.84 | 0.34 | −1.15 | −2.10 |
| 4 | 0.22 | 0.22 | −0.01 | −0.11 | −0.20 | 1.37 | 2.49 | −0.15 | −1.50 | −2.08 |
| Big | 0.03 | 0.08 | 0.01 | −0.01 | −0.09 | 0.17 | 1.19 | 0.11 | −0.12 | −0.90 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | 0.57 | −0.06 | −0.06 | −0.15 | −0.63 | 3.58 | −0.66 | −0.69 | −1.26 | −4.16 |
| 2 | 0.58 | 0.27 | 0.00 | −0.17 | −0.37 | 4.66 | 3.93 | −0.03 | −2.48 | −3.62 |
| 3 | 0.59 | 0.15 | 0.06 | −0.06 | −0.30 | 4.50 | 2.07 | 0.83 | −0.89 | −2.75 |
| 4 | 0.50 | 0.34 | 0.03 | −0.05 | −0.20 | 3.50 | 3.91 | 0.42 | −0.55 | −1.75 |
| Big | 0.26 | 0.10 | 0.01 | −0.06 | −0.17 | 1.73 | 1.25 | 0.23 | −0.76 | −1.67 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | 0.48 | −0.11 | −0.12 | −0.15 | −0.50 | 2.78 | −1.19 | −1.29 | −1.66 | −3.76 |
| 2 | 0.38 | 0.12 | −0.08 | −0.17 | −0.21 | 2.60 | 1.49 | −1.37 | −2.42 | −1.86 |
| 3 | 0.38 | 0.00 | −0.09 | −0.12 | −0.17 | 2.77 | −0.01 | −1.21 | −1.76 | −1.43 |
| 4 | 0.28 | 0.15 | −0.08 | −0.14 | −0.10 | 1.86 | 1.86 | −0.99 | −1.60 | −0.95 |
| Big | 0.07 | 0.04 | −0.04 | 0.00 | −0.10 | 0.46 | 0.52 | −0.68 | −0.01 | −0.98 |

Table 1.A3: Average excess returns and alphas of the 25 size-CI portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-CI (abnormal capital investment) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.82 | 0.87 | 1.05 | 0.89 | 0.70 | 2.67 | 3.00 | 3.62 | 3.17 | 2.36 |
| 2 | 0.76 | 0.85 | 0.87 | 0.88 | 0.66 | 2.75 | 3.20 | 3.39 | 3.50 | 2.50 |
| 3 | 0.82 | 0.90 | 0.83 | 0.80 | 0.56 | 3.28 | 3.76 | 3.45 | 3.16 | 2.22 |
| 4 | 0.71 | 0.73 | 0.74 | 0.68 | 0.56 | 2.97 | 3.28 | 3.43 | 2.84 | 2.16 |
| Big | 0.60 | 0.55 | 0.44 | 0.41 | 0.51 | 2.71 | 2.71 | 2.37 | 2.12 | 2.41 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.21 | 0.31 | 0.48 | 0.32 | 0.12 | 1.24 | 1.85 | 3.01 | 2.14 | 0.73 |
| 2 | 0.14 | 0.27 | 0.30 | 0.31 | 0.06 | 0.97 | 1.97 | 2.28 | 2.31 | 0.45 |
| 3 | 0.22 | 0.35 | 0.28 | 0.23 | −0.03 | 1.96 | 3.15 | 2.62 | 2.17 | −0.24 |
| 4 | 0.15 | 0.19 | 0.21 | 0.13 | −0.03 | 1.54 | 2.08 | 2.36 | 1.32 | −0.23 |
| Big | 0.08 | 0.06 | 0.01 | −0.06 | 0.00 | 0.89 | 1.00 | 0.12 | −0.89 | −0.06 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | −0.02 | 0.03 | 0.20 | 0.06 | −0.12 | −0.27 | 0.45 | 2.91 | 0.69 | −1.55 |
| 2 | −0.03 | 0.04 | 0.08 | 0.08 | −0.11 | −0.32 | 0.45 | 1.12 | 1.03 | −1.34 |
| 3 | 0.11 | 0.18 | 0.10 | 0.02 | −0.18 | 1.34 | 2.41 | 1.23 | 0.26 | −2.10 |
| 4 | 0.04 | 0.06 | 0.10 | 0.00 | −0.10 | 0.43 | 0.75 | 1.21 | 0.03 | −0.97 |
| Big | 0.18 | 0.11 | 0.03 | −0.05 | 0.02 | 2.10 | 1.64 | 0.57 | −0.82 | 0.24 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.14 | 0.19 | 0.34 | 0.24 | 0.06 | 1.28 | 2.10 | 4.32 | 3.09 | 0.64 |
| 2 | 0.10 | 0.17 | 0.21 | 0.19 | 0.06 | 1.30 | 2.27 | 2.83 | 2.26 | 0.78 |
| 3 | 0.22 | 0.27 | 0.18 | 0.17 | −0.01 | 2.66 | 3.52 | 2.31 | 2.35 | −0.19 |
| 4 | 0.12 | 0.19 | 0.21 | 0.12 | 0.07 | 1.38 | 2.57 | 2.74 | 1.51 | 0.66 |
| Big | 0.24 | 0.16 | 0.10 | 0.04 | 0.10 | 2.32 | 2.29 | 1.85 | 0.69 | 1.19 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | −0.02 | 0.01 | 0.19 | 0.07 | −0.13 | −0.23 | 0.18 | 2.84 | 0.86 | −1.79 |
| 2 | 0.00 | 0.03 | 0.09 | 0.08 | −0.13 | −0.05 | 0.38 | 1.16 | 0.99 | −1.65 |
| 3 | 0.12 | 0.16 | 0.08 | 0.00 | −0.19 | 1.59 | 2.24 | 1.07 | −0.03 | −2.30 |
| 4 | 0.02 | 0.05 | 0.08 | −0.03 | −0.12 | 0.27 | 0.63 | 1.07 | −0.39 | −1.22 |
| Big | 0.18 | 0.10 | 0.03 | −0.05 | 0.01 | 2.07 | 1.49 | 0.65 | −0.92 | 0.08 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | −0.01 | 0.06 | 0.24 | 0.09 | −0.11 | −0.18 | 0.90 | 3.69 | 1.23 | −1.67 |
| 2 | −0.03 | 0.07 | 0.12 | 0.13 | −0.11 | −0.35 | 0.98 | 1.72 | 1.58 | −1.51 |
| 3 | 0.10 | 0.21 | 0.14 | 0.04 | −0.18 | 1.35 | 2.98 | 1.96 | 0.62 | −2.26 |
| 4 | 0.06 | 0.07 | 0.11 | 0.02 | −0.13 | 0.69 | 0.93 | 1.46 | 0.21 | −1.31 |
| Big | 0.11 | 0.07 | 0.00 | −0.06 | −0.01 | 1.26 | 1.14 | 0.07 | −1.13 | −0.09 |

*(Continued)*

Table 1.1A3 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.29 | 0.25 | 0.40 | 0.27 | 0.19 | 1.82 | 1.75 | 3.23 | 1.79 | 1.28 |
| 2 | 0.11 | 0.11 | 0.16 | 0.11 | 0.06 | 0.94 | 0.84 | 1.45 | 1.06 | 0.61 |
| 3 | 0.21 | 0.21 | 0.08 | 0.06 | −0.04 | 1.99 | 2.29 | 0.78 | 0.61 | −0.35 |
| 4 | 0.06 | 0.12 | 0.11 | 0.04 | 0.04 | 0.68 | 1.07 | 1.28 | 0.41 | 0.34 |
| Big | 0.31 | 0.17 | 0.03 | −0.07 | 0.14 | 2.18 | 2.19 | 0.41 | −1.12 | 1.66 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.10 | 0.06 | 0.23 | 0.09 | −0.03 | 0.87 | 0.56 | 2.51 | 0.83 | −0.31 |
| 2 | 0.01 | −0.01 | 0.08 | 0.02 | −0.08 | 0.08 | −0.08 | 0.91 | 0.23 | −0.87 |
| 3 | 0.14 | 0.14 | 0.01 | −0.04 | −0.16 | 1.47 | 1.81 | 0.17 | −0.54 | −1.64 |
| 4 | 0.03 | 0.03 | 0.02 | −0.07 | −0.07 | 0.38 | 0.31 | 0.31 | −0.85 | −0.71 |
| Big | 0.29 | 0.14 | −0.02 | −0.13 | 0.07 | 2.56 | 2.01 | −0.35 | −2.31 | 0.85 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.09 | 0.05 | 0.22 | 0.08 | −0.04 | 0.83 | 0.46 | 2.31 | 0.69 | −0.37 |
| 2 | 0.01 | −0.01 | 0.07 | 0.01 | −0.08 | 0.06 | −0.15 | 0.76 | 0.13 | −0.89 |
| 3 | 0.14 | 0.14 | 0.01 | −0.05 | −0.17 | 1.43 | 1.77 | 0.08 | −0.59 | −1.60 |
| 4 | 0.03 | 0.02 | 0.02 | −0.07 | −0.08 | 0.33 | 0.23 | 0.26 | −0.91 | −0.74 |
| Big | 0.29 | 0.14 | −0.02 | −0.13 | 0.07 | 2.54 | 2.01 | −0.35 | −2.30 | 0.84 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | 0.12 | 0.12 | 0.26 | 0.17 | 0.04 | 0.84 | 1.07 | 2.56 | 1.72 | 0.35 |
| 2 | 0.09 | 0.06 | 0.15 | 0.03 | 0.03 | 0.90 | 0.75 | 1.68 | 0.42 | 0.39 |
| 3 | 0.26 | 0.18 | 0.08 | 0.09 | 0.01 | 2.71 | 2.19 | 0.92 | 0.99 | 0.07 |
| 4 | 0.13 | 0.19 | 0.14 | 0.08 | 0.13 | 1.36 | 2.34 | 1.70 | 0.78 | 1.26 |
| Big | 0.28 | 0.15 | 0.07 | −0.01 | 0.12 | 1.92 | 1.85 | 0.96 | −0.15 | 1.28 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | 0.22 | 0.13 | 0.27 | 0.16 | 0.09 | 1.62 | 1.20 | 2.94 | 1.56 | 0.84 |
| 2 | 0.06 | −0.02 | 0.07 | −0.02 | 0.00 | 0.65 | −0.28 | 0.86 | −0.30 | 0.01 |
| 3 | 0.18 | 0.12 | −0.03 | −0.07 | −0.13 | 1.88 | 1.59 | −0.37 | −1.02 | −1.52 |
| 4 | 0.02 | 0.02 | 0.06 | −0.03 | 0.01 | 0.16 | 0.24 | 0.74 | −0.32 | 0.14 |
| Big | 0.35 | 0.16 | 0.03 | −0.03 | 0.18 | 2.42 | 1.91 | 0.39 | −0.47 | 1.99 |

Table 1.A4: Average excess returns and alphas of the 25 size-DR portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-DR (distress risk) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.64 | 0.72 | 0.77 | 0.73 | 0.72 | 2.45 | 2.47 | 2.63 | 2.40 | 2.03 |
| 2 | 0.71 | 0.69 | 0.79 | 0.76 | 0.70 | 2.86 | 2.71 | 3.02 | 2.76 | 2.11 |
| 3 | 0.72 | 0.67 | 0.70 | 0.70 | 0.76 | 3.10 | 2.77 | 2.91 | 2.60 | 2.40 |
| 4 | 0.63 | 0.70 | 0.64 | 0.61 | 0.87 | 2.83 | 2.96 | 2.89 | 2.38 | 2.74 |
| Big | 0.47 | 0.53 | 0.48 | 0.47 | 0.60 | 2.53 | 2.71 | 2.33 | 1.94 | 1.98 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.12 | 0.17 | 0.19 | 0.14 | 0.07 | 0.88 | 0.95 | 1.22 | 0.84 | 0.35 |
| 2 | 0.17 | 0.12 | 0.20 | 0.16 | 0.02 | 1.40 | 0.91 | 1.65 | 1.13 | 0.11 |
| 3 | 0.18 | 0.12 | 0.14 | 0.11 | 0.10 | 1.87 | 1.15 | 1.35 | 0.91 | 0.59 |
| 4 | 0.10 | 0.15 | 0.11 | 0.05 | 0.24 | 1.22 | 1.56 | 1.29 | 0.39 | 1.28 |
| Big | 0.03 | 0.07 | −0.01 | −0.06 | 0.00 | 0.44 | 0.95 | −0.11 | −0.56 | −0.01 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | −0.03 | 0.02 | 0.02 | −0.12 | −0.35 | −0.43 | 0.19 | 0.24 | −1.50 | −3.41 |
| 2 | 0.07 | 0.00 | 0.04 | −0.09 | −0.41 | 0.98 | −0.04 | 0.54 | −1.07 | −3.88 |
| 3 | 0.14 | 0.01 | −0.04 | −0.13 | −0.30 | 1.92 | 0.10 | −0.54 | −1.56 | −2.91 |
| 4 | 0.12 | 0.07 | −0.04 | −0.20 | −0.12 | 1.64 | 0.74 | −0.54 | −2.17 | −0.82 |
| Big | 0.14 | 0.02 | −0.11 | −0.28 | −0.39 | 3.20 | 0.37 | −1.69 | −3.47 | −3.18 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.06 | 0.14 | 0.16 | 0.05 | −0.09 | 0.72 | 1.23 | 1.90 | 0.56 | −0.77 |
| 2 | 0.13 | 0.07 | 0.17 | 0.10 | −0.10 | 1.98 | 0.74 | 2.40 | 1.30 | −1.03 |
| 3 | 0.23 | 0.09 | 0.10 | 0.05 | −0.04 | 3.22 | 0.99 | 1.44 | 0.59 | −0.39 |
| 4 | 0.20 | 0.15 | 0.08 | −0.02 | 0.09 | 2.64 | 1.77 | 1.05 | −0.20 | 0.53 |
| Big | 0.17 | 0.07 | −0.01 | −0.10 | −0.18 | 3.06 | 1.18 | −0.10 | −1.24 | −1.41 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | −0.04 | 0.02 | 0.02 | −0.11 | −0.33 | −0.48 | 0.22 | 0.34 | −1.44 | −3.32 |
| 2 | 0.08 | 0.01 | 0.02 | −0.09 | −0.41 | 1.08 | 0.15 | 0.35 | −1.13 | −4.04 |
| 3 | 0.14 | 0.02 | −0.05 | −0.14 | −0.29 | 1.92 | 0.22 | −0.69 | −1.71 | −2.86 |
| 4 | 0.11 | 0.04 | −0.06 | −0.22 | −0.12 | 1.47 | 0.40 | −0.76 | −2.46 | −0.83 |
| Big | 0.14 | 0.02 | −0.14 | −0.27 | −0.35 | 3.21 | 0.30 | −2.11 | −3.31 | −2.97 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | −0.02 | 0.02 | 0.01 | −0.10 | −0.29 | −0.25 | 0.17 | 0.20 | −1.35 | −3.05 |
| 2 | 0.08 | 0.01 | 0.04 | −0.07 | −0.36 | 1.12 | 0.07 | 0.67 | −1.02 | −4.69 |
| 3 | 0.12 | 0.02 | −0.02 | −0.11 | −0.24 | 1.70 | 0.28 | −0.29 | −1.48 | −2.55 |
| 4 | 0.09 | 0.07 | −0.02 | −0.16 | −0.04 | 1.22 | 0.81 | −0.35 | −2.19 | −0.32 |
| Big | 0.09 | 0.02 | −0.10 | −0.24 | −0.28 | 1.99 | 0.40 | −1.60 | −3.08 | −2.10 |

*(Continued)*

Table 1.A4 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.04 | 0.14 | 0.22 | 0.14 | 0.06 | 0.29 | 0.91 | 1.68 | 0.99 | 0.35 |
| 2 | 0.04 | −0.02 | 0.18 | 0.09 | −0.01 | 0.40 | −0.17 | 1.59 | 0.66 | −0.03 |
| 3 | 0.11 | 0.00 | 0.04 | 0.12 | 0.00 | 1.02 | 0.02 | 0.39 | 0.96 | −0.03 |
| 4 | 0.09 | 0.02 | 0.07 | −0.06 | 0.07 | 0.95 | 0.18 | 0.82 | −0.56 | 0.43 |
| Big | 0.09 | 0.04 | −0.05 | −0.16 | −0.20 | 1.26 | 0.59 | −0.58 | −1.46 | −1.23 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | −0.05 | 0.05 | 0.08 | −0.05 | −0.25 | −0.53 | 0.37 | 0.89 | −0.52 | −1.86 |
| 2 | 0.02 | −0.05 | 0.08 | −0.05 | −0.31 | 0.25 | −0.51 | 0.92 | −0.52 | −2.25 |
| 3 | 0.10 | −0.02 | −0.04 | −0.04 | −0.26 | 1.23 | −0.21 | −0.52 | −0.41 | −2.25 |
| 4 | 0.09 | −0.01 | −0.04 | −0.21 | −0.11 | 1.12 | −0.15 | −0.50 | −2.17 | −0.73 |
| Big | 0.09 | −0.01 | −0.14 | −0.25 | −0.29 | 1.59 | −0.19 | −1.90 | −2.83 | −2.17 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | −0.05 | 0.04 | 0.08 | −0.06 | −0.27 | −0.55 | 0.35 | 0.83 | −0.57 | −1.81 |
| 2 | 0.02 | −0.05 | 0.07 | −0.06 | −0.33 | 0.24 | −0.53 | 0.79 | −0.56 | −1.99 |
| 3 | 0.10 | −0.02 | −0.05 | −0.05 | −0.28 | 1.22 | −0.25 | −0.54 | −0.48 | −2.01 |
| 4 | 0.09 | −0.02 | −0.05 | −0.22 | −0.13 | 1.13 | −0.18 | −0.55 | −2.10 | −0.80 |
| Big | 0.09 | −0.01 | −0.14 | −0.26 | −0.31 | 1.61 | −0.23 | −1.75 | −2.47 | −1.99 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | −0.01 | 0.14 | 0.15 | 0.01 | −0.11 | −0.13 | 0.98 | 1.42 | 0.13 | −0.74 |
| 2 | 0.03 | −0.05 | 0.19 | 0.10 | −0.09 | 0.37 | −0.51 | 2.37 | 1.24 | −0.67 |
| 3 | 0.17 | 0.07 | 0.10 | 0.16 | −0.02 | 2.11 | 0.63 | 1.31 | 1.64 | −0.16 |
| 4 | 0.21 | 0.15 | 0.11 | 0.02 | 0.08 | 2.59 | 1.69 | 1.18 | 0.22 | 0.48 |
| Big | 0.13 | 0.07 | 0.03 | −0.01 | −0.14 | 1.57 | 0.96 | 0.41 | −0.05 | −0.98 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | −0.02 | 0.09 | 0.16 | 0.02 | −0.14 | −0.18 | 0.76 | 1.65 | 0.23 | −1.12 |
| 2 | 0.00 | −0.08 | 0.08 | −0.05 | −0.26 | 0.01 | −0.90 | 0.97 | −0.56 | −2.68 |
| 3 | 0.09 | −0.07 | −0.08 | −0.07 | −0.25 | 1.08 | −0.65 | −1.23 | −0.76 | −2.75 |
| 4 | 0.13 | −0.04 | −0.06 | −0.22 | −0.12 | 1.67 | −0.44 | −0.73 | −2.41 | −0.67 |
| Big | 0.15 | −0.01 | −0.15 | −0.31 | −0.41 | 2.21 | −0.22 | −2.16 | −3.45 | −2.88 |

Table 1.A5: Average excess returns and alphas of the 25 size-$\beta$ portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-$\beta$ (market beta) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.66 | 0.83 | 0.81 | 0.88 | 0.63 | 3.24 | 3.61 | 2.98 | 2.99 | 1.68 |
| 2 | 0.65 | 0.81 | 0.90 | 0.80 | 0.58 | 3.49 | 3.94 | 3.87 | 3.01 | 1.72 |
| 3 | 0.67 | 0.84 | 0.81 | 0.74 | 0.62 | 4.01 | 4.02 | 3.58 | 2.82 | 1.85 |
| 4 | 0.65 | 0.79 | 0.72 | 0.52 | 0.65 | 3.80 | 3.79 | 3.17 | 1.99 | 1.96 |
| Big | 0.52 | 0.54 | 0.47 | 0.45 | 0.33 | 3.33 | 2.89 | 2.26 | 1.68 | 1.02 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.29 | 0.39 | 0.31 | 0.29 | −0.10 | 2.19 | 2.63 | 1.84 | 1.79 | −0.48 |
| 2 | 0.28 | 0.37 | 0.38 | 0.21 | −0.18 | 2.44 | 3.10 | 2.93 | 1.49 | −1.10 |
| 3 | 0.32 | 0.38 | 0.29 | 0.15 | −0.14 | 3.55 | 3.58 | 2.67 | 1.18 | −1.01 |
| 4 | 0.30 | 0.32 | 0.19 | −0.08 | −0.11 | 2.98 | 3.55 | 1.83 | −0.72 | −0.75 |
| Big | 0.19 | 0.10 | −0.04 | −0.15 | −0.37 | 2.19 | 1.31 | −0.66 | −1.69 | −2.39 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | 0.05 | 0.12 | 0.03 | 0.04 | −0.26 | 0.66 | 1.74 | 0.48 | 0.71 | −2.52 |
| 2 | 0.04 | 0.13 | 0.16 | 0.00 | −0.29 | 0.56 | 1.99 | 2.04 | 0.00 | −3.34 |
| 3 | 0.13 | 0.21 | 0.11 | −0.03 | −0.19 | 1.74 | 2.98 | 1.64 | −0.38 | −2.02 |
| 4 | 0.15 | 0.18 | 0.06 | −0.19 | −0.13 | 1.68 | 2.45 | 0.82 | −2.25 | −1.05 |
| Big | 0.13 | 0.09 | −0.04 | −0.16 | −0.29 | 1.90 | 1.46 | −0.63 | −1.77 | −1.95 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.04 | 0.10 | 0.00 | 0.06 | −0.16 | 0.50 | 1.33 | 0.03 | 1.01 | −1.48 |
| 2 | 0.00 | 0.11 | 0.15 | 0.01 | −0.16 | −0.06 | 1.61 | 2.08 | 0.19 | −1.92 |
| 3 | 0.08 | 0.18 | 0.10 | 0.01 | −0.06 | 0.99 | 2.50 | 1.53 | 0.07 | −0.68 |
| 4 | 0.09 | 0.17 | 0.07 | −0.13 | 0.00 | 0.99 | 2.36 | 0.91 | −1.49 | −0.01 |
| Big | 0.07 | 0.05 | 0.00 | −0.09 | −0.14 | 1.04 | 0.88 | −0.03 | −1.07 | −0.98 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | 0.05 | 0.14 | 0.05 | 0.05 | −0.26 | 0.69 | 1.99 | 0.70 | 0.95 | −2.63 |
| 2 | 0.04 | 0.13 | 0.16 | 0.00 | −0.30 | 0.54 | 1.96 | 2.13 | −0.01 | −3.44 |
| 3 | 0.13 | 0.22 | 0.11 | −0.04 | −0.20 | 1.78 | 3.16 | 1.61 | −0.43 | −2.12 |
| 4 | 0.14 | 0.17 | 0.05 | −0.20 | −0.16 | 1.60 | 2.31 | 0.63 | −2.38 | −1.28 |
| Big | 0.16 | 0.08 | −0.04 | −0.20 | −0.31 | 2.26 | 1.23 | −0.61 | −2.13 | −2.14 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | 0.14 | 0.23 | 0.14 | 0.11 | −0.27 | 1.58 | 2.72 | 1.61 | 1.69 | −2.54 |
| 2 | 0.15 | 0.23 | 0.24 | 0.07 | −0.32 | 1.62 | 2.99 | 2.90 | 0.87 | −3.57 |
| 3 | 0.22 | 0.29 | 0.19 | 0.03 | −0.23 | 2.77 | 3.66 | 2.49 | 0.34 | −2.52 |
| 4 | 0.22 | 0.24 | 0.12 | −0.16 | −0.18 | 2.35 | 3.05 | 1.36 | −1.87 | −1.40 |
| Big | 0.18 | 0.11 | −0.04 | −0.17 | −0.36 | 2.40 | 1.68 | −0.58 | −1.88 | −2.36 |

*(Continued)*

Table 1.A5 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.10 | 0.09 | 0.06 | 0.16 | 0.12 | 1.03 | 0.84 | 0.74 | 2.26 | 0.85 |
| 2 | 0.00 | 0.04 | 0.08 | −0.05 | −0.06 | −0.04 | 0.46 | 0.80 | −0.68 | −0.58 |
| 3 | 0.02 | 0.09 | 0.00 | −0.07 | −0.01 | 0.20 | 1.17 | 0.05 | −0.74 | −0.05 |
| 4 | −0.02 | 0.04 | −0.10 | −0.21 | 0.19 | −0.17 | 0.42 | −1.26 | −2.19 | 1.37 |
| Big | −0.12 | −0.08 | −0.09 | −0.04 | −0.05 | −1.38 | −1.27 | −1.12 | −0.42 | −0.32 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.08 | 0.07 | 0.02 | 0.07 | −0.07 | 1.07 | 1.09 | 0.28 | 1.34 | −0.72 |
| 2 | 0.03 | 0.04 | 0.08 | −0.07 | −0.20 | 0.33 | 0.73 | 1.14 | −1.08 | −2.33 |
| 3 | 0.08 | 0.11 | 0.02 | −0.10 | −0.10 | 1.11 | 1.77 | 0.33 | −1.29 | −1.09 |
| 4 | 0.05 | 0.04 | −0.08 | −0.26 | 0.02 | 0.57 | 0.51 | −1.18 | −3.00 | 0.19 |
| Big | −0.07 | −0.06 | −0.11 | −0.13 | −0.11 | -0.95 | −1.03 | −1.74 | −1.29 | −0.71 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.07 | 0.06 | 0.01 | 0.07 | −0.07 | 0.79 | 0.79 | 0.19 | 1.15 | −0.69 |
| 2 | 0.02 | 0.03 | 0.07 | −0.07 | −0.19 | 0.18 | 0.47 | 0.91 | −1.08 | −2.29 |
| 3 | 0.07 | 0.11 | 0.02 | −0.11 | −0.10 | 0.84 | 1.57 | 0.24 | −1.34 | −1.04 |
| 4 | 0.04 | 0.03 | −0.08 | −0.26 | 0.03 | 0.49 | 0.43 | −1.22 | −2.98 | 0.20 |
| Big | −0.07 | −0.06 | −0.11 | −0.13 | −0.11 | −0.95 | −1.04 | −1.81 | −1.37 | −0.70 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | −0.04 | −0.04 | −0.10 | 0.00 | −0.10 | −0.44 | −0.44 | −1.12 | −0.03 | −0.75 |
| 2 | −0.09 | −0.03 | 0.02 | −0.07 | −0.11 | −0.93 | −0.37 | 0.27 | −0.89 | −1.04 |
| 3 | 0.03 | 0.06 | 0.02 | −0.05 | −0.02 | 0.32 | 0.76 | 0.20 | −0.46 | −0.13 |
| 4 | 0.09 | 0.06 | −0.03 | −0.13 | 0.14 | 0.85 | 0.64 | −0.39 | −1.30 | 1.16 |
| Big | −0.06 | −0.13 | −0.05 | −0.03 | 0.09 | −0.68 | −1.91 | −0.66 | −0.37 | 0.55 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | −0.04 | −0.06 | −0.06 | 0.06 | 0.14 | −0.45 | −0.72 | −0.68 | 0.90 | 1.05 |
| 2 | −0.18 | −0.11 | −0.06 | −0.16 | −0.02 | −1.93 | −1.67 | −0.73 | −2.52 | −0.22 |
| 3 | −0.15 | −0.01 | −0.12 | −0.16 | 0.04 | −1.74 | −0.14 | −1.69 | −1.61 | 0.36 |
| 4 | −0.17 | −0.06 | −0.17 | −0.27 | 0.25 | −1.60 | −0.73 | −2.37 | −2.93 | 1.73 |
| Big | −0.18 | −0.10 | −0.11 | −0.05 | 0.08 | −2.10 | −1.44 | −1.59 | −0.47 | 0.48 |

## Table 1.A6: Average excess returns and alphas of the 35 size-NI portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 35 size-NI (net share issues) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Neg | Zero | Low | 1 | 2 | 3 | High | Neg | Zero | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | | | $t$-statistic (average excess returns) | | | | | | |
| Small | 0.97 | 0.64 | 0.79 | 0.88 | 0.92 | 0.56 | 0.10 | 3.67 | 2.35 | 2.75 | 2.92 | 2.95 | 1.75 | 0.27 |
| 2 | 0.83 | 0.82 | 0.82 | 0.80 | 0.80 | 0.75 | 0.22 | 3.63 | 3.14 | 3.27 | 2.98 | 2.93 | 2.73 | 0.74 |
| 3 | 0.90 | 0.68 | 0.77 | 0.84 | 0.77 | 0.69 | 0.21 | 4.06 | 2.60 | 3.37 | 3.51 | 3.03 | 2.66 | 0.72 |
| 4 | 0.92 | 0.61 | 0.61 | 0.69 | 0.77 | 0.54 | 0.24 | 4.34 | 2.97 | 2.66 | 2.96 | 3.10 | 2.14 | 0.87 |
| Big | 0.62 | 0.68 | 0.49 | 0.48 | 0.58 | 0.38 | 0.20 | 3.51 | 3.55 | 2.56 | 2.50 | 2.72 | 1.54 | 0.81 |
| | CAPM $\alpha$ | | | | | | | $t$-statistic (CAPM $\alpha$) | | | | | | |
| Small | 0.47 | 0.16 | 0.24 | 0.31 | 0.31 | −0.08 | −0.58 | 2.96 | 0.93 | 1.46 | 1.81 | 1.81 | −0.45 | −2.97 |
| 2 | 0.34 | 0.33 | 0.27 | 0.22 | 0.19 | 0.12 | −0.46 | 2.61 | 1.95 | 2.08 | 1.63 | 1.52 | 0.99 | −3.09 |
| 3 | 0.40 | 0.19 | 0.26 | 0.28 | 0.19 | 0.09 | −0.43 | 3.73 | 1.28 | 2.21 | 2.69 | 1.85 | 0.84 | −3.54 |
| 4 | 0.42 | 0.20 | 0.10 | 0.14 | 0.21 | −0.04 | −0.37 | 4.22 | 1.56 | 0.97 | 1.44 | 2.31 | −0.44 | −2.97 |
| Big | 0.19 | 0.33 | 0.07 | 0.01 | 0.08 | −0.17 | −0.31 | 2.75 | 2.47 | 0.78 | 0.19 | 0.99 | −1.63 | −2.96 |
| | FF3 $\alpha$ | | | | | | | $t$-statistic (FF3 $\alpha$) | | | | | | |
| Small | 0.18 | −0.09 | −0.02 | 0.07 | 0.15 | −0.20 | −0.63 | 2.58 | −1.01 | −0.29 | 0.95 | 1.87 | −2.62 | −6.07 |
| 2 | 0.09 | 0.10 | 0.04 | 0.04 | 0.06 | 0.05 | −0.46 | 1.31 | 0.89 | 0.51 | 0.59 | 0.91 | 0.74 | −4.74 |
| 3 | 0.22 | −0.04 | 0.04 | 0.13 | 0.10 | 0.04 | −0.40 | 2.90 | −0.28 | 0.46 | 1.90 | 1.45 | 0.49 | −4.57 |
| 4 | 0.25 | 0.07 | −0.06 | 0.04 | 0.20 | −0.02 | −0.36 | 3.27 | 0.47 | −0.81 | 0.46 | 2.51 | −0.20 | −3.33 |
| Big | 0.15 | 0.25 | 0.07 | 0.07 | 0.15 | −0.02 | −0.34 | 2.73 | 1.77 | 0.95 | 0.96 | 1.84 | −0.26 | −3.26 |
| | FFC $\alpha$ | | | | | | | $t$-statistic (FFC $\alpha$) | | | | | | |
| Small | 0.16 | −0.11 | 0.00 | 0.09 | 0.16 | −0.17 | −0.58 | 2.33 | −1.10 | −0.07 | 1.26 | 2.08 | −2.23 | −5.66 |
| 2 | 0.09 | 0.06 | 0.08 | 0.03 | 0.07 | 0.07 | −0.40 | 1.45 | 0.53 | 1.06 | 0.48 | 1.06 | 1.02 | −4.45 |
| 3 | 0.21 | 0.00 | 0.03 | 0.14 | 0.10 | 0.05 | −0.31 | 2.93 | −0.02 | 0.32 | 2.01 | 1.31 | 0.70 | −3.57 |
| 4 | 0.27 | 0.04 | −0.02 | 0.09 | 0.18 | −0.02 | −0.31 | 3.69 | 0.27 | −0.25 | 1.05 | 2.17 | −0.18 | −2.97 |
| Big | 0.15 | 0.24 | 0.03 | 0.09 | 0.12 | 0.01 | −0.23 | 2.74 | 1.72 | 0.46 | 1.18 | 1.44 | 0.06 | −2.25 |
| | FFPS $\alpha$ | | | | | | | $t$-statistic (FFPS $\alpha$) | | | | | | |
| Small | 0.21 | −0.09 | −0.01 | 0.07 | 0.16 | −0.20 | −0.63 | 2.91 | −0.96 | −0.17 | 1.07 | 1.97 | −2.57 | −6.21 |
| 2 | 0.10 | 0.09 | 0.04 | 0.03 | 0.05 | 0.04 | −0.45 | 1.52 | 0.79 | 0.56 | 0.52 | 0.77 | 0.61 | −4.74 |
| 3 | 0.21 | −0.03 | 0.03 | 0.12 | 0.10 | 0.02 | −0.41 | 2.95 | −0.25 | 0.32 | 1.74 | 1.41 | 0.25 | −4.66 |
| 4 | 0.23 | 0.07 | −0.08 | 0.02 | 0.18 | −0.04 | −0.40 | 3.12 | 0.52 | −1.02 | 0.26 | 2.16 | −0.39 | −3.69 |
| Big | 0.15 | 0.27 | 0.07 | 0.05 | 0.12 | −0.06 | −0.33 | 2.60 | 1.93 | 0.96 | 0.77 | 1.42 | −0.66 | −3.08 |
| | FFAF $\alpha$ | | | | | | | $t$-statistic (FFAF $\alpha$) | | | | | | |
| Small | 0.29 | −0.01 | 0.06 | 0.14 | 0.18 | −0.19 | −0.67 | 3.50 | −0.08 | 0.77 | 1.74 | 2.14 | −2.44 | −6.40 |
| 2 | 0.18 | 0.20 | 0.11 | 0.10 | 0.10 | 0.05 | −0.51 | 2.47 | 1.52 | 1.41 | 1.36 | 1.31 | 0.77 | −4.97 |
| 3 | 0.29 | 0.04 | 0.14 | 0.18 | 0.13 | 0.04 | −0.47 | 3.79 | 0.29 | 1.49 | 2.49 | 1.77 | 0.54 | −4.98 |
| 4 | 0.32 | 0.11 | −0.01 | 0.06 | 0.20 | −0.04 | −0.41 | 4.00 | 0.84 | −0.18 | 0.73 | 2.47 | −0.47 | −3.65 |
| Big | 0.18 | 0.29 | 0.09 | 0.04 | 0.13 | −0.10 | −0.35 | 2.93 | 2.07 | 1.20 | 0.65 | 1.59 | −1.04 | −3.47 |
| | HXZ $\alpha$ | | | | | | | $t$-statistic (HXZ $\alpha$) | | | | | | |
| Small | 0.13 | −0.05 | 0.07 | 0.13 | 0.33 | 0.02 | −0.25 | 1.38 | −0.38 | 0.73 | 1.45 | 3.18 | 0.21 | −2.05 |
| 2 | −0.02 | −0.02 | 0.00 | 0.00 | 0.08 | 0.17 | −0.19 | −0.20 | −0.15 | 0.03 | −0.04 | 1.11 | 2.29 | −1.98 |
| 3 | 0.05 | −0.14 | −0.07 | 0.09 | 0.12 | 0.11 | −0.08 | 0.58 | −0.87 | −0.59 | 1.27 | 1.57 | 1.39 | −1.02 |
| 4 | 0.09 | −0.11 | −0.18 | −0.03 | 0.21 | 0.13 | 0.00 | 1.00 | −0.73 | −2.05 | −0.42 | 2.46 | 1.13 | −0.02 |
| Big | 0.00 | 0.08 | −0.11 | 0.08 | 0.18 | 0.17 | −0.16 | 0.07 | 0.52 | −1.46 | 1.02 | 1.96 | 1.67 | −1.27 |

*(Continued)*

Table 1.A6 – *Continued*

| | Neg | Zero | Low | 1 | 2 | 3 | High | Neg | Zero | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FF5 $\alpha$ | | | | | | | $t$-statistic (FF5 $\alpha$) | | | | | | |
| Small | 0.11 | −0.13 | −0.03 | 0.06 | 0.22 | −0.07 | −0.39 | 1.77 | −1.30 | −0.38 | 0.91 | 2.62 | −1.00 | −4.44 |
| 2 | −0.04 | 0.04 | −0.02 | −0.03 | 0.06 | 0.16 | −0.24 | −0.79 | 0.32 | −0.27 | −0.50 | 0.87 | 2.39 | −2.51 |
| 3 | 0.06 | −0.10 | −0.05 | 0.06 | 0.11 | 0.14 | −0.13 | 0.95 | −0.71 | −0.63 | 0.98 | 1.45 | 1.82 | −1.64 |
| 4 | 0.08 | −0.13 | −0.21 | −0.07 | 0.21 | 0.12 | −0.06 | 1.15 | −1.01 | −2.72 | −0.85 | 2.40 | 1.21 | −0.61 |
| Big | 0.01 | 0.06 | −0.09 | 0.04 | 0.18 | 0.15 | −0.17 | 0.24 | 0.39 | −1.27 | 0.62 | 2.10 | 1.81 | −1.55 |
| | FF4 $\alpha$ | | | | | | | $t$-statistic (FF4 $\alpha$) | | | | | | |
| Small | 0.10 | −0.13 | −0.03 | 0.06 | 0.22 | −0.07 | −0.38 | 1.40 | −1.28 | −0.44 | 0.83 | 2.58 | −0.99 | −3.98 |
| 2 | −0.05 | 0.03 | −0.03 | −0.03 | 0.06 | 0.16 | −0.23 | −0.78 | 0.23 | −0.33 | −0.52 | 0.86 | 2.39 | −2.53 |
| 3 | 0.05 | −0.11 | −0.06 | 0.06 | 0.11 | 0.14 | −0.13 | 0.81 | −0.72 | −0.65 | 0.94 | 1.45 | 1.82 | −1.65 |
| 4 | 0.07 | −0.14 | −0.21 | −0.07 | 0.21 | 0.12 | −0.07 | 1.02 | −1.01 | −2.77 | −0.89 | 2.33 | 1.21 | −0.63 |
| Big | 0.01 | 0.06 | −0.09 | 0.05 | 0.18 | 0.16 | −0.17 | 0.24 | 0.39 | −1.25 | 0.63 | 2.11 | 1.81 | −1.51 |
| | SY4 $\alpha$ | | | | | | | $t$-statistic (SY4 $\alpha$) | | | | | | |
| Small | −0.01 | −0.19 | −0.13 | 0.00 | 0.13 | −0.14 | −0.41 | −0.19 | −1.75 | −1.35 | −0.02 | 1.22 | −1.37 | −3.26 |
| 2 | −0.11 | −0.14 | 0.00 | −0.06 | −0.04 | 0.10 | −0.19 | −1.54 | −1.11 | −0.02 | −0.72 | −0.51 | 1.20 | −1.78 |
| 3 | 0.04 | −0.08 | −0.07 | 0.07 | 0.07 | 0.11 | −0.01 | 0.49 | −0.56 | −0.58 | 0.96 | 0.86 | 1.36 | −0.07 |
| 4 | 0.10 | −0.18 | −0.14 | 0.04 | 0.19 | 0.12 | 0.05 | 1.30 | −1.23 | −1.33 | 0.41 | 2.27 | 1.39 | 0.52 |
| Big | −0.03 | 0.19 | −0.08 | 0.05 | 0.11 | 0.30 | 0.10 | −0.64 | 1.18 | −1.15 | 0.69 | 1.36 | 3.15 | 1.02 |
| | BS6 $\alpha$ | | | | | | | $t$-statistic (BS6 $\alpha$) | | | | | | |
| Small | −0.01 | −0.19 | −0.04 | 0.06 | 0.32 | 0.03 | −0.17 | −0.18 | −1.82 | −0.46 | 0.77 | 3.06 | 0.32 | −1.46 |
| 2 | −0.16 | −0.22 | −0.10 | −0.07 | 0.05 | 0.18 | −0.15 | −2.49 | −1.86 | −1.28 | −0.94 | 0.65 | 2.27 | −1.57 |
| 3 | −0.06 | −0.23 | −0.21 | 0.03 | 0.08 | 0.08 | −0.04 | −0.80 | −1.54 | −1.86 | 0.37 | 1.05 | 0.99 | −0.52 |
| 4 | 0.00 | −0.22 | −0.28 | −0.10 | 0.21 | 0.17 | −0.01 | −0.03 | −1.39 | −3.16 | −1.17 | 2.16 | 1.41 | −0.08 |
| Big | −0.03 | 0.00 | −0.11 | 0.09 | 0.19 | 0.25 | −0.21 | −0.44 | −0.03 | −1.48 | 1.10 | 2.02 | 2.28 | −1.91 |

Table 1.A7: Average excess returns and alphas of the 25 size-MAX portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-MAX (lottery demand) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.84 | 1.18 | 1.11 | 0.88 | 0.09 | 3.97 | 4.69 | 3.92 | 2.90 | 0.24 |
| 2 | 1.03 | 1.01 | 0.95 | 0.70 | 0.23 | 5.02 | 4.46 | 3.60 | 2.44 | 0.67 |
| 3 | 0.85 | 0.88 | 0.84 | 0.65 | 0.27 | 4.27 | 3.94 | 3.41 | 2.37 | 0.82 |
| 4 | 0.73 | 0.76 | 0.70 | 0.60 | 0.44 | 3.93 | 3.66 | 3.01 | 2.20 | 1.38 |
| Big | 0.46 | 0.54 | 0.44 | 0.57 | 0.50 | 2.76 | 3.10 | 2.10 | 2.35 | 1.51 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.49 | 0.71 | 0.57 | 0.29 | −0.61 | 3.41 | 4.87 | 3.63 | 1.76 | −3.12 |
| 2 | 0.63 | 0.52 | 0.39 | 0.06 | −0.54 | 5.13 | 4.40 | 2.85 | 0.44 | −3.30 |
| 3 | 0.46 | 0.39 | 0.28 | 0.01 | −0.47 | 3.94 | 3.50 | 2.47 | 0.11 | −3.07 |
| 4 | 0.34 | 0.28 | 0.15 | −0.03 | −0.28 | 3.49 | 2.93 | 1.48 | −0.34 | −1.87 |
| Big | 0.11 | 0.10 | −0.07 | 0.00 | −0.18 | 1.32 | 1.66 | −1.00 | 0.00 | −1.13 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | 0.28 | 0.46 | 0.32 | 0.05 | −0.79 | 2.65 | 5.07 | 3.64 | 0.61 | −7.85 |
| 2 | 0.41 | 0.30 | 0.17 | −0.12 | −0.57 | 4.67 | 4.44 | 2.14 | −1.80 | −6.38 |
| 3 | 0.25 | 0.18 | 0.12 | −0.13 | −0.44 | 3.00 | 2.34 | 1.50 | −1.92 | −4.27 |
| 4 | 0.16 | 0.12 | 0.02 | −0.10 | −0.21 | 2.10 | 1.41 | 0.28 | −1.32 | −1.75 |
| Big | 0.05 | 0.08 | −0.06 | 0.02 | −0.12 | 0.70 | 1.54 | −0.87 | 0.25 | −0.78 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.31 | 0.54 | 0.42 | 0.20 | −0.54 | 3.24 | 7.12 | 5.46 | 2.42 | −4.26 |
| 2 | 0.43 | 0.33 | 0.22 | −0.03 | −0.40 | 5.30 | 4.97 | 3.19 | −0.50 | −3.74 |
| 3 | 0.28 | 0.21 | 0.16 | −0.07 | −0.32 | 3.49 | 2.86 | 2.12 | −0.97 | −2.99 |
| 4 | 0.18 | 0.15 | 0.07 | −0.03 | −0.05 | 2.32 | 1.90 | 0.99 | −0.36 | −0.37 |
| Big | 0.01 | 0.06 | −0.05 | 0.09 | −0.06 | 0.14 | 1.02 | −0.79 | 0.91 | −0.37 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | 0.27 | 0.47 | 0.33 | 0.06 | −0.80 | 2.65 | 5.21 | 3.79 | 0.73 | −8.07 |
| 2 | 0.39 | 0.30 | 0.17 | −0.09 | −0.56 | 4.61 | 4.52 | 2.26 | −1.47 | −6.25 |
| 3 | 0.24 | 0.17 | 0.12 | −0.13 | −0.43 | 2.94 | 2.31 | 1.58 | −1.88 | −4.11 |
| 4 | 0.14 | 0.11 | 0.01 | −0.12 | −0.24 | 1.96 | 1.36 | 0.13 | −1.46 | −1.94 |
| Big | 0.06 | 0.09 | −0.06 | 0.00 | −0.13 | 0.87 | 1.62 | −0.96 | 0.04 | −0.83 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | 0.35 | 0.53 | 0.37 | 0.07 | −0.85 | 3.33 | 5.92 | 4.39 | 1.02 | −8.15 |
| 2 | 0.49 | 0.38 | 0.23 | −0.09 | −0.65 | 5.37 | 5.18 | 2.86 | −1.42 | −6.52 |
| 3 | 0.33 | 0.26 | 0.16 | −0.10 | −0.52 | 3.63 | 3.18 | 2.05 | −1.41 | −4.80 |
| 4 | 0.23 | 0.18 | 0.06 | −0.10 | −0.33 | 2.82 | 2.15 | 0.75 | −1.33 | −2.46 |
| Big | 0.10 | 0.11 | −0.05 | −0.01 | −0.18 | 1.33 | 1.92 | −0.87 | −0.13 | −1.17 |

*(Continued)*

Table 1.A7 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.24 | 0.46 | 0.37 | 0.21 | −0.28 | 1.80 | 3.72 | 2.92 | 1.58 | −1.57 |
| 2 | 0.34 | 0.21 | 0.11 | −0.11 | −0.18 | 3.09 | 2.33 | 1.07 | −1.26 | −1.67 |
| 3 | 0.12 | 0.03 | 0.00 | −0.12 | −0.07 | 1.13 | 0.32 | 0.02 | −1.48 | −0.59 |
| 4 | 0.00 | −0.02 | −0.09 | −0.03 | 0.17 | −0.04 | −0.17 | −1.18 | −0.32 | 1.26 |
| Big | −0.12 | −0.09 | −0.11 | 0.12 | 0.23 | −1.36 | −1.67 | −1.54 | 1.23 | 1.44 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.19 | 0.39 | 0.27 | 0.06 | −0.54 | 1.79 | 4.21 | 2.84 | 0.61 | −4.20 |
| 2 | 0.30 | 0.19 | 0.08 | −0.15 | −0.31 | 4.11 | 3.22 | 1.04 | −2.07 | −4.01 |
| 3 | 0.11 | 0.03 | −0.01 | −0.16 | −0.16 | 1.46 | 0.51 | −0.09 | −2.23 | −1.72 |
| 4 | 0.00 | −0.03 | −0.10 | −0.09 | 0.06 | 0.04 | −0.37 | −1.54 | −1.08 | 0.50 |
| Big | −0.10 | −0.06 | −0.08 | 0.09 | 0.14 | −1.41 | −1.14 | −1.23 | 1.00 | 0.94 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.18 | 0.38 | 0.26 | 0.05 | −0.55 | 1.58 | 3.65 | 2.49 | 0.51 | −4.24 |
| 2 | 0.29 | 0.18 | 0.07 | −0.15 | −0.31 | 3.34 | 2.63 | 0.84 | −2.02 | −3.84 |
| 3 | 0.10 | 0.02 | −0.01 | −0.16 | −0.16 | 1.17 | 0.31 | −0.16 | −2.28 | −1.63 |
| 4 | −0.01 | −0.04 | −0.10 | −0.09 | 0.06 | −0.06 | −0.43 | −1.58 | −1.11 | 0.52 |
| Big | −0.10 | −0.06 | −0.08 | 0.09 | 0.14 | −1.42 | −1.19 | −1.24 | 0.98 | 0.95 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | 0.15 | 0.39 | 0.30 | 0.16 | −0.35 | 1.49 | 4.84 | 3.55 | 1.93 | −2.15 |
| 2 | 0.25 | 0.17 | 0.10 | −0.04 | −0.17 | 2.94 | 2.51 | 1.32 | −0.56 | −1.45 |
| 3 | 0.12 | 0.05 | 0.03 | −0.07 | −0.01 | 1.50 | 0.55 | 0.37 | −0.79 | −0.07 |
| 4 | 0.05 | 0.05 | 0.02 | 0.03 | 0.24 | 0.50 | 0.54 | 0.27 | 0.31 | 1.67 |
| Big | −0.12 | −0.09 | −0.08 | 0.20 | 0.27 | −1.46 | −1.24 | −1.20 | 2.11 | 1.65 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | 0.12 | 0.32 | 0.24 | 0.11 | −0.31 | 1.08 | 3.66 | 2.80 | 1.22 | −2.06 |
| 2 | 0.18 | 0.06 | −0.02 | −0.18 | −0.09 | 2.03 | 0.96 | −0.27 | −2.88 | −0.88 |
| 3 | −0.04 | −0.13 | −0.10 | −0.19 | 0.05 | −0.49 | −1.61 | −1.25 | −2.43 | 0.41 |
| 4 | −0.13 | −0.13 | −0.17 | −0.06 | 0.31 | −1.43 | −1.37 | −2.12 | −0.74 | 2.48 |
| Big | −0.17 | −0.12 | −0.12 | 0.11 | 0.27 | −1.93 | −1.77 | −1.66 | 1.11 | 1.68 |

Table 1.A8: Average excess returns and alphas of the 25 size-RVar portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-RVar (residual variance) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 1.02 | 1.09 | 0.96 | 0.67 | −0.41 | 4.69 | 4.05 | 3.05 | 1.87 | −0.97 |
| 2 | 0.91 | 1.00 | 1.00 | 0.86 | 0.08 | 4.68 | 4.14 | 3.79 | 2.85 | 0.20 |
| 3 | 0.76 | 0.90 | 0.83 | 0.86 | 0.24 | 4.21 | 4.13 | 3.45 | 3.14 | 0.70 |
| 4 | 0.73 | 0.74 | 0.73 | 0.73 | 0.32 | 4.23 | 3.73 | 3.19 | 2.92 | 0.97 |
| Big | 0.47 | 0.53 | 0.51 | 0.49 | 0.39 | 2.98 | 3.01 | 2.60 | 2.21 | 1.34 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.66 | 0.58 | 0.36 | −0.01 | −1.16 | 4.53 | 3.68 | 2.16 | −0.07 | −4.71 |
| 2 | 0.53 | 0.50 | 0.43 | 0.20 | −0.72 | 4.47 | 3.62 | 3.05 | 1.37 | −4.02 |
| 3 | 0.40 | 0.42 | 0.30 | 0.25 | −0.53 | 3.82 | 3.64 | 2.34 | 1.89 | −3.50 |
| 4 | 0.38 | 0.29 | 0.20 | 0.14 | −0.42 | 3.76 | 2.76 | 2.04 | 1.35 | −3.17 |
| Big | 0.11 | 0.10 | 0.03 | −0.05 | −0.27 | 1.74 | 1.70 | 0.42 | −0.73 | −2.31 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | 0.38 | 0.29 | 0.08 | −0.25 | −1.36 | 3.98 | 3.18 | 0.83 | −2.54 | −8.64 |
| 2 | 0.28 | 0.22 | 0.19 | 0.01 | −0.76 | 3.45 | 2.71 | 1.97 | 0.17 | −6.97 |
| 3 | 0.18 | 0.20 | 0.09 | 0.08 | −0.50 | 2.27 | 2.38 | 0.98 | 0.94 | −5.13 |
| 4 | 0.19 | 0.12 | 0.05 | 0.03 | −0.36 | 2.22 | 1.41 | 0.64 | 0.40 | −3.22 |
| Big | 0.08 | 0.12 | 0.01 | −0.05 | −0.12 | 1.32 | 2.10 | 0.21 | −0.74 | −1.14 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | 0.42 | 0.37 | 0.25 | 0.02 | −1.01 | 5.06 | 4.48 | 2.79 | 0.19 | −5.52 |
| 2 | 0.28 | 0.26 | 0.24 | 0.12 | −0.55 | 3.70 | 3.38 | 2.70 | 1.48 | −4.28 |
| 3 | 0.17 | 0.23 | 0.13 | 0.13 | −0.35 | 2.24 | 2.99 | 1.59 | 1.34 | −3.38 |
| 4 | 0.19 | 0.16 | 0.09 | 0.09 | −0.23 | 2.16 | 2.05 | 1.30 | 0.94 | −2.05 |
| Big | 0.05 | 0.06 | −0.02 | −0.05 | −0.05 | 0.70 | 1.00 | −0.29 | −0.86 | −0.43 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | 0.38 | 0.30 | 0.07 | −0.26 | −1.37 | 4.02 | 3.40 | 0.82 | −2.68 | −8.68 |
| 2 | 0.28 | 0.23 | 0.20 | 0.03 | −0.75 | 3.44 | 2.87 | 2.16 | 0.35 | −6.88 |
| 3 | 0.17 | 0.19 | 0.09 | 0.09 | −0.49 | 2.17 | 2.39 | 1.00 | 1.04 | −4.99 |
| 4 | 0.18 | 0.11 | 0.04 | 0.04 | −0.39 | 2.12 | 1.34 | 0.48 | 0.45 | −3.52 |
| Big | 0.08 | 0.13 | 0.02 | −0.06 | −0.13 | 1.32 | 2.23 | 0.38 | −0.89 | −1.18 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | 0.48 | 0.37 | 0.11 | −0.28 | −1.45 | 4.65 | 3.98 | 1.37 | −3.19 | −8.73 |
| 2 | 0.39 | 0.32 | 0.26 | 0.04 | −0.85 | 4.15 | 3.56 | 2.75 | 0.48 | −7.37 |
| 3 | 0.28 | 0.28 | 0.16 | 0.13 | −0.59 | 3.17 | 3.14 | 1.69 | 1.48 | −5.80 |
| 4 | 0.27 | 0.19 | 0.11 | 0.06 | −0.45 | 3.01 | 2.00 | 1.30 | 0.72 | −4.00 |
| Big | 0.12 | 0.14 | 0.04 | −0.04 | −0.22 | 1.93 | 2.53 | 0.56 | −0.66 | −1.93 |

*(Continued)*

Table 1.A8 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.31 | 0.24 | 0.19 | 0.14 | −0.55 | 2.40 | 1.85 | 1.35 | 0.84 | −2.50 |
| 2 | 0.16 | 0.06 | 0.03 | −0.03 | −0.27 | 1.50 | 0.54 | 0.24 | −0.25 | −2.24 |
| 3 | 0.01 | 0.05 | −0.09 | −0.01 | −0.14 | 0.15 | 0.50 | −0.80 | −0.12 | −1.35 |
| 4 | 0.02 | −0.05 | −0.10 | −0.07 | 0.01 | 0.20 | −0.52 | −1.08 | −0.69 | 0.07 |
| Big | −0.04 | −0.10 | −0.14 | −0.05 | 0.21 | −0.63 | −1.51 | −2.19 | −0.77 | 1.99 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.28 | 0.16 | 0.04 | −0.12 | −0.95 | 3.14 | 1.97 | 0.42 | −0.97 | −5.46 |
| 2 | 0.16 | 0.05 | 0.04 | −0.07 | −0.47 | 2.21 | 0.82 | 0.44 | −0.89 | −4.72 |
| 3 | 0.03 | 0.06 | −0.08 | −0.04 | −0.25 | 0.49 | 0.78 | −1.01 | −0.50 | −2.87 |
| 4 | 0.03 | −0.05 | −0.11 | −0.08 | −0.11 | 0.38 | −0.69 | −1.47 | −0.90 | −1.11 |
| Big | −0.01 | −0.03 | −0.10 | −0.04 | 0.10 | −0.13 | −0.57 | −1.69 | −0.59 | 1.13 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.27 | 0.15 | 0.03 | −0.13 | −0.96 | 2.43 | 1.59 | 0.29 | −1.01 | −0.52 |
| 2 | 0.15 | 0.05 | 0.03 | −0.08 | −0.47 | 1.66 | 0.56 | 0.32 | −0.92 | −4.67 |
| 3 | 0.02 | 0.05 | −0.09 | −0.05 | −0.25 | 0.29 | 0.53 | −0.99 | −0.56 | −2.71 |
| 4 | 0.02 | −0.06 | −0.11 | −0.08 | −0.11 | 0.25 | −0.72 | −1.47 | −0.92 | −1.04 |
| Big | −0.01 | −0.03 | −0.10 | −0.04 | 0.11 | −0.18 | −0.53 | −1.70 | −0.61 | 1.16 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | 0.23 | 0.19 | 0.18 | 0.11 | −0.68 | 2.58 | 2.25 | 1.80 | 0.75 | −3.01 |
| 2 | 0.07 | 0.04 | 0.09 | 0.07 | −0.27 | 0.79 | 0.52 | 0.97 | 0.84 | −1.94 |
| 3 | 0.00 | 0.07 | −0.02 | 0.06 | −0.06 | 0.01 | 0.80 | −0.27 | 0.57 | −0.54 |
| 4 | 0.04 | 0.03 | 0.00 | 0.06 | 0.07 | 0.39 | 0.35 | 0.02 | 0.54 | 0.60 |
| Big | −0.08 | −0.08 | −0.12 | −0.02 | 0.25 | −1.12 | −1.19 | −1.77 | −0.24 | 2.23 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | 0.13 | 0.06 | 0.05 | 0.06 | −0.57 | 1.50 | 0.74 | 0.54 | 0.49 | −2.74 |
| 2 | −0.02 | −0.12 | −0.11 | −0.12 | −0.17 | −0.24 | −1.56 | −1.24 | −1.50 | −1.49 |
| 3 | −0.15 | −0.12 | −0.23 | −0.11 | −0.04 | −1.78 | −1.35 | −2.76 | −1.08 | −0.35 |
| 4 | −0.13 | −0.17 | −0.21 | −0.13 | 0.12 | −1.26 | −1.96 | −2.59 | −1.25 | 0.97 |
| Big | −0.09 | −0.10 | −0.17 | −0.08 | 0.32 | −1.22 | −1.33 | −2.42 | −1.14 | 2.84 |

Table 1.A9: Average excess returns and alphas of the 25 size-AC portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 25 size-AC (accruals) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. All $t$-statistics are adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average excess returns | | | | | $t$-statistic (average excess returns) | | | | |
| Small | 0.72 | 0.85 | 0.73 | 0.85 | 0.42 | 2.20 | 2.91 | 2.61 | 2.92 | 1.26 |
| 2 | 0.73 | 0.78 | 0.78 | 0.65 | 0.54 | 2.54 | 3.11 | 3.18 | 2.58 | 1.86 |
| 3 | 0.76 | 0.75 | 0.77 | 0.71 | 0.49 | 2.82 | 3.30 | 3.36 | 2.86 | 1.70 |
| 4 | 0.65 | 0.63 | 0.59 | 0.73 | 0.64 | 2.63 | 2.87 | 2.71 | 3.17 | 2.33 |
| Big | 0.60 | 0.51 | 0.50 | 0.47 | 0.21 | 2.68 | 2.76 | 2.88 | 2.36 | 0.94 |
| | CAPM $\alpha$ | | | | | $t$-statistic (CAPM $\alpha$) | | | | |
| Small | 0.09 | 0.27 | 0.18 | 0.27 | −0.22 | 0.50 | 1.70 | 1.13 | 1.69 | −1.23 |
| 2 | 0.09 | 0.21 | 0.23 | 0.07 | −0.11 | 0.69 | 1.74 | 1.90 | 0.60 | −0.81 |
| 3 | 0.14 | 0.21 | 0.25 | 0.14 | −0.16 | 1.20 | 2.18 | 2.46 | 1.42 | −1.37 |
| 4 | 0.08 | 0.10 | 0.08 | 0.20 | 0.01 | 0.70 | 1.30 | 1.06 | 2.11 | 0.05 |
| Big | 0.08 | 0.07 | 0.08 | 0.00 | −0.31 | 0.82 | 1.07 | 1.46 | −0.01 | −3.07 |
| | FF3 $\alpha$ | | | | | $t$-statistic (FF3 $\alpha$) | | | | |
| Small | −0.06 | 0.12 | 0.02 | 0.12 | −0.37 | −0.70 | 1.51 | 0.29 | 1.70 | −5.06 |
| 2 | −0.02 | 0.10 | 0.11 | −0.04 | −0.19 | −0.36 | 1.46 | 1.68 | −0.57 | −2.58 |
| 3 | 0.08 | 0.15 | 0.15 | 0.04 | −0.22 | 0.96 | 2.19 | 2.16 | 0.57 | −2.51 |
| 4 | 0.05 | 0.05 | −0.01 | 0.16 | 0.00 | 0.59 | 0.62 | −0.18 | 2.11 | 0.03 |
| Big | 0.21 | 0.15 | 0.11 | 0.07 | −0.21 | 2.54 | 2.74 | 2.20 | 0.98 | −2.07 |
| | FFC $\alpha$ | | | | | $t$-statistic (FFC $\alpha$) | | | | |
| Small | −0.03 | 0.15 | 0.01 | 0.13 | −0.32 | −0.30 | 1.77 | 0.10 | 1.96 | −4.09 |
| 2 | 0.00 | 0.12 | 0.11 | −0.02 | −0.14 | 0.03 | 1.99 | 1.72 | −0.25 | −2.07 |
| 3 | 0.09 | 0.19 | 0.17 | 0.07 | −0.14 | 1.07 | 2.71 | 2.41 | 1.09 | −1.58 |
| 4 | 0.07 | 0.08 | 0.02 | 0.16 | 0.04 | 0.74 | 1.10 | 0.24 | 2.29 | 0.48 |
| Big | 0.19 | 0.15 | 0.11 | 0.08 | −0.16 | 2.16 | 2.65 | 2.23 | 1.16 | −1.55 |
| | FFPS $\alpha$ | | | | | $t$-statistic (FFPS $\alpha$) | | | | |
| Small | −0.07 | 0.12 | 0.02 | 0.11 | −0.38 | −0.81 | 1.45 | 0.27 | 1.53 | −5.15 |
| 2 | −0.03 | 0.09 | 0.10 | −0.05 | −0.19 | −0.52 | 1.29 | 1.57 | −0.69 | −2.61 |
| 3 | 0.09 | 0.14 | 0.13 | 0.00 | −0.23 | 0.98 | 1.95 | 1.84 | 0.06 | −2.62 |
| 4 | 0.04 | 0.03 | −0.05 | 0.14 | −0.03 | 0.48 | 0.34 | −0.77 | 1.81 | −0.32 |
| Big | 0.20 | 0.14 | 0.11 | 0.05 | −0.22 | 2.33 | 2.42 | 2.09 | 0.69 | −2.17 |
| | FFAF $\alpha$ | | | | | $t$-statistic (FFAF $\alpha$) | | | | |
| Small | −0.05 | 0.14 | 0.06 | 0.15 | −0.36 | −0.55 | 1.66 | 0.74 | 2.03 | −4.97 |
| 2 | −0.01 | 0.11 | 0.14 | −0.02 | −0.19 | −0.17 | 1.71 | 2.05 | −0.24 | −2.67 |
| 3 | 0.08 | 0.14 | 0.18 | 0.06 | −0.24 | 0.97 | 2.12 | 2.48 | 0.87 | −2.84 |
| 4 | 0.05 | 0.05 | 0.01 | 0.17 | −0.02 | 0.51 | 0.70 | 0.19 | 2.03 | −0.25 |
| Big | 0.15 | 0.12 | 0.10 | 0.04 | −0.26 | 1.65 | 1.93 | 1.98 | 0.64 | −2.48 |

*(Continued)*

Table 1.A9 – *Continued*

| | Low | 1 | 2 | 3 | High | Low | 1 | 2 | 3 | High |
|---|---|---|---|---|---|---|---|---|---|---|
| | HXZ $\alpha$ | | | | | $t$-statistic (HXZ $\alpha$) | | | | |
| Small | 0.17 | 0.34 | 0.16 | 0.28 | −0.12 | 1.52 | 3.37 | 1.98 | 3.47 | −1.42 |
| 2 | 0.05 | 0.11 | 0.14 | 0.02 | −0.08 | 0.81 | 1.51 | 2.02 | 0.23 | −1.05 |
| 3 | 0.12 | 0.21 | 0.18 | 0.05 | −0.14 | 1.34 | 2.69 | 2.22 | 0.71 | −1.30 |
| 4 | 0.06 | 0.08 | 0.00 | 0.16 | 0.11 | 0.63 | 1.14 | 0.04 | 1.78 | 1.15 |
| Big | 0.25 | 0.21 | 0.02 | 0.09 | −0.19 | 2.30 | 3.27 | 0.30 | 1.14 | −1.85 |
| | FF5 $\alpha$ | | | | | $t$-statistic (FF5 $\alpha$) | | | | |
| Small | 0.05 | 0.25 | 0.10 | 0.19 | −0.25 | 0.58 | 3.41 | 1.33 | 2.56 | −3.50 |
| 2 | 0.03 | 0.09 | 0.12 | −0.04 | −0.15 | 0.46 | 1.37 | 1.87 | −0.60 | −2.16 |
| 3 | 0.13 | 0.18 | 0.15 | 0.02 | −0.21 | 1.44 | 2.56 | 2.05 | 0.34 | −2.42 |
| 4 | 0.03 | 0.05 | −0.05 | 0.13 | 0.03 | 0.30 | 0.75 | −0.59 | 1.48 | 0.33 |
| Big | 0.24 | 0.18 | 0.00 | 0.04 | −0.23 | 2.83 | 3.13 | 0.03 | 0.54 | −2.40 |
| | FF4 $\alpha$ | | | | | $t$-statistic (FF4 $\alpha$) | | | | |
| Small | 0.05 | 0.25 | 0.10 | 0.19 | −0.25 | 0.59 | 3.39 | 1.32 | 2.55 | −3.53 |
| 2 | 0.03 | 0.09 | 0.12 | −0.04 | −0.15 | 0.46 | 1.38 | 1.87 | −0.58 | −2.15 |
| 3 | 0.13 | 0.19 | 0.15 | 0.02 | −0.21 | 1.44 | 2.58 | 2.05 | 0.31 | −2.40 |
| 4 | 0.03 | 0.06 | −0.05 | 0.13 | 0.03 | 0.33 | 0.76 | −0.63 | 1.44 | 0.34 |
| Big | 0.25 | 0.18 | 0.00 | 0.04 | −0.23 | 2.68 | 3.11 | 0.09 | 0.58 | −2.37 |
| | SY4 $\alpha$ | | | | | $t$-statistic (SY4 $\alpha$) | | | | |
| Small | −0.02 | 0.16 | −0.01 | 0.06 | −0.28 | −0.14 | 1.57 | −0.12 | 0.72 | −2.74 |
| 2 | 0.03 | 0.05 | 0.03 | −0.11 | −0.14 | 0.42 | 0.72 | 0.37 | −1.34 | −1.64 |
| 3 | 0.17 | 0.18 | 0.11 | 0.02 | −0.08 | 1.70 | 2.30 | 1.41 | 0.20 | −0.92 |
| 4 | 0.11 | 0.10 | −0.02 | 0.12 | 0.07 | 1.07 | 1.28 | −0.25 | 1.49 | 0.74 |
| Big | 0.26 | 0.14 | 0.02 | 0.02 | −0.06 | 2.31 | 1.73 | 0.46 | 0.31 | −0.55 |
| | BS6 $\alpha$ | | | | | $t$-statistic (BS6 $\alpha$) | | | | |
| Small | 0.19 | 0.33 | 0.16 | 0.26 | −0.14 | 1.82 | 3.33 | 1.74 | 3.25 | −1.83 |
| 2 | 0.04 | 0.08 | 0.12 | 0.01 | −0.10 | 0.54 | 1.20 | 1.77 | 0.09 | −1.42 |
| 3 | 0.12 | 0.22 | 0.16 | 0.01 | −0.17 | 1.25 | 2.78 | 1.98 | 0.12 | −1.75 |
| 4 | 0.07 | 0.08 | −0.04 | 0.17 | 0.10 | 0.66 | 1.06 | −0.43 | 1.65 | 1.03 |
| Big | 0.30 | 0.25 | 0.03 | 0.13 | −0.14 | 2.79 | 3.66 | 0.56 | 1.64 | −1.33 |

Table 1.A10: Average excess returns and alphas of the 30 IND portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 30 IND (industry) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| Industry | Average excess returns | CAPM $\alpha$ | FF3 $\alpha$ | FFC $\alpha$ | FFPS $\alpha$ | FFAF $\alpha$ | HXZ $\alpha$ | FF5 $\alpha$ | FF4 $\alpha$ | SY4 $\alpha$ | BS6 $\alpha$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Food | 0.68 | 0.34 | 0.30 | 0.29 | 0.29 | 0.33 | −0.02 | −0.01 | 0.00 | −0.01 | −0.05 |
| | (3.64) | (2.40) | (2.23) | (2.17) | (2.10) | (2.38) | (−0.16) | (−0.05) | (−0.04) | (−0.07) | (−0.32) |
| Beer | 0.74 | 0.37 | 0.36 | 0.29 | 0.37 | 0.40 | −0.02 | 0.04 | 0.04 | −0.01 | 0.00 |
| | (3.44) | (2.25) | (2.16) | (1.78) | (2.14) | (2.46) | (−0.10) | (0.24) | (0.27) | (−0.05) | (−0.02) |
| Smoke | 1.06 | 0.74 | 0.70 | 0.70 | 0.75 | 0.72 | 0.31 | 0.27 | 0.27 | 0.22 | 0.30 |
| | (4.10) | (3.03) | (2.94) | (3.07) | (3.22) | (2.99) | (1.29) | (1.15) | (1.18) | (0.88) | (1.20) |
| Games | 0.68 | 0.03 | −0.07 | 0.10 | −0.09 | −0.10 | 0.04 | −0.14 | −0.14 | 0.06 | −0.03 |
| | (2.12) | (0.17) | (−0.45) | (0.63) | (−0.56) | (−0.60) | (0.20) | (−0.83) | (−0.86) | (0.33) | (−0.16) |
| Books | 0.42 | −0.11 | −0.27 | −0.22 | −0.29 | −0.22 | −0.38 | −0.43 | −0.44 | −0.38 | −0.48 |
| | (1.51) | (−0.75) | (−2.01) | (−1.60) | (−2.09) | (−1.59) | (−2.68) | (−3.22) | (−3.24) | (−2.67) | (−3.52) |
| Hshld | 0.43 | 0.03 | 0.06 | 0.04 | 0.07 | 0.08 | −0.22 | −0.20 | −0.20 | −0.25 | −0.18 |
| | (2.12) | (0.25) | (0.51) | (0.36) | (0.53) | (0.57) | (−1.75) | (−1.82) | (−1.81) | (−1.87) | (−1.37) |
| Clths | 0.63 | 0.08 | −0.12 | 0.06 | −0.13 | −0.07 | −0.27 | −0.31 | −0.32 | −0.18 | −0.39 |
| | (2.09) | (0.43) | (−0.62) | (0.36) | (−0.70) | (−0.40) | (−1.21) | (−1.73) | (−1.79) | (−0.97) | (−2.09) |
| Hlth | 0.64 | 0.23 | 0.41 | 0.36 | 0.45 | 0.37 | 0.06 | 0.20 | 0.21 | 0.17 | 0.26 |
| | (3.19) | (1.74) | (3.49) | (2.89) | (3.71) | (3.13) | (0.41) | (1.56) | (1.54) | (1.17) | (1.81) |
| Chems | 0.58 | 0.07 | −0.09 | −0.01 | −0.13 | −0.03 | −0.19 | −0.25 | −0.26 | −0.14 | −0.25 |
| | (2.44) | (0.48) | (−0.62) | (−0.04) | (−0.94) | (−0.25) | (−1.13) | (−1.79) | (−1.82) | (−0.82) | (−1.47) |
| Txtls | 0.60 | 0.04 | −0.36 | −0.11 | −0.34 | −0.28 | −0.35 | −0.57 | −0.58 | −0.44 | −0.59 |
| | (1.84) | (0.17) | (−1.93) | (−0.62) | (−1.82) | (−1.49) | (−1.50) | (−3.13) | (−2.89) | (−2.23) | (−2.89) |
| Cnstr | 0.54 | −0.05 | −0.28 | −0.26 | −0.28 | −0.19 | −0.44 | −0.46 | −0.47 | −0.40 | −0.62 |
| | (2.01) | (−0.36) | (−2.30) | (−2.16) | (−2.37) | (−1.51) | (−2.95) | (−3.67) | (−3.46) | (−2.58) | (−4.32) |
| Steel | 0.32 | −0.32 | −0.52 | −0.42 | −0.58 | −0.48 | −0.10 | −0.36 | −0.36 | −0.25 | −0.22 |
| | (1.01) | (−1.46) | (−2.57) | (−2.19) | (−2.81) | (−2.32) | (−0.52) | (−1.79) | (−1.80) | (−1.20) | (−1.09) |
| FabPr | 0.53 | −0.07 | −0.16 | −0.04 | −0.20 | −0.16 | −0.05 | −0.17 | −0.17 | 0.01 | −0.07 |
| | (1.92) | (−0.50) | (−1.11) | (−0.27) | (−1.42) | (−1.15) | (−0.32) | (−1.14) | (−1.14) | (0.07) | (−0.49) |
| ElcEq | 0.69 | 0.09 | 0.09 | 0.11 | 0.10 | 0.08 | 0.04 | 0.03 | 0.03 | 0.02 | 0.04 |
| | (2.65) | (0.82) | (0.75) | (0.94) | (0.86) | (0.67) | (0.37) | (0.27) | (0.27) | (0.19) | (0.29) |

*(Continued)*

Table 1.A10 – *Continued*

| Industry | Average excess returns | CAPM $\alpha$ | FF3 $\alpha$ | FFC $\alpha$ | FFPS $\alpha$ | FFAF $\alpha$ | HXZ $\alpha$ | FF5 $\alpha$ | FF4 $\alpha$ | SY4 $\alpha$ | BS6 $\alpha$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Autos | 0.42 | −0.14 | −0.46 | −0.20 | −0.52 | −0.43 | −0.19 | −0.49 | −0.51 | −0.32 | −0.42 |
| | (1.35) | (−0.71) | (−2.60) | (−1.09) | (−2.86) | (−2.67) | (−0.90) | (−2.66) | (−2.58) | (−1.64) | (−2.22) |
| Carry | 0.66 | 0.10 | −0.05 | 0.02 | −0.05 | 0.00 | −0.20 | −0.27 | −0.28 | −0.09 | −0.30 |
| | (2.27) | (0.57) | (−0.32) | (0.13) | (−0.31) | (−0.02) | (−1.09) | (−1.67) | (−1.69) | (−0.50) | (−1.69) |
| Mines | 0.40 | −0.06 | −0.22 | −0.21 | −0.26 | −0.17 | −0.13 | −0.30 | −0.30 | −0.12 | −0.27 |
| | (1.25) | (−0.24) | (−0.82) | (−0.80) | (−0.95) | (−0.64) | (−0.45) | (−1.05) | (−1.06) | (−0.44) | (−0.89) |
| Coal | 0.66 | 0.07 | −0.11 | −0.19 | −0.28 | −0.06 | −0.13 | −0.21 | −0.21 | 0.15 | −0.37 |
| | (1.31) | (0.16) | (−0.23) | (−0.41) | (−0.61) | (−0.13) | (−0.26) | (−0.44) | (−0.44) | (0.26) | (−0.70) |
| Oil | 0.62 | 0.23 | 0.12 | 0.04 | 0.10 | 0.18 | 0.00 | −0.02 | −0.02 | 0.20 | −0.16 |
| | (2.75) | (1.31) | (0.71) | (0.23) | (0.55) | (1.03) | (0.02) | (−0.11) | (−0.13) | (1.11) | (−0.93) |
| Util | 0.48 | 0.23 | 0.07 | 0.01 | 0.05 | 0.13 | −0.09 | −0.06 | −0.06 | 0.07 | −0.31 |
| | (2.78) | (1.67) | (0.58) | (0.09) | (0.39) | (1.06) | (−0.59) | (−0.43) | (−0.46) | (0.46) | (−1.95) |
| Telcm | 0.55 | 0.16 | 0.11 | 0.18 | 0.10 | 0.09 | 0.34 | 0.17 | 0.17 | 0.25 | 0.27 |
| | (2.63) | (1.13) | (0.85) | (1.28) | (0.79) | (0.67) | (2.33) | (1.32) | (1.27) | (1.82) | (1.84) |
| Servs | 0.60 | −0.04 | 0.16 | 0.22 | 0.18 | 0.03 | 0.39 | 0.34 | 0.34 | 0.26 | 0.49 |
| | (2.14) | (−0.32) | (1.50) | (2.09) | (1.69) | (0.30) | (2.88) | (3.03) | (2.93) | (1.98) | (3.78) |
| BusEq | 0.48 | −0.16 | 0.07 | 0.20 | 0.04 | −0.07 | 0.50 | 0.35 | 0.36 | 0.25 | 0.74 |
| | (1.56) | (−0.92) | (0.47) | (1.45) | (0.30) | (−0.45) | (2.99) | (2.65) | (2.54) | (1.39) | (4.65) |
| Paper | 0.55 | 0.08 | −0.05 | 0.01 | −0.05 | 0.01 | −0.29 | −0.27 | −0.28 | −0.25 | −0.34 |
| | (2.60) | (0.63) | (−0.43) | (0.05) | (−0.48) | (0.05) | (−2.40) | (−2.55) | (−2.52) | (−1.92) | (−2.79) |
| Trans | 0.53 | 0.01 | −0.16 | −0.10 | −0.14 | −0.08 | −0.23 | −0.30 | −0.30 | −0.19 | −0.34 |
| | (2.12) | (0.06) | (−1.17) | (−0.78) | (−1.01) | (−0.62) | (−1.39) | (−2.33) | (−2.25) | (−1.42) | (−2.22) |
| Whlsl | 0.52 | 0.00 | −0.08 | −0.07 | −0.05 | −0.04 | −0.25 | −0.25 | −0.25 | −0.17 | −0.28 |
| | (2.09) | (−0.01) | (−0.72) | (−0.52) | (−0.44) | (−0.40) | (−1.88) | (−2.28) | (−2.27) | (−1.19) | (−2.00) |
| Rtail | 0.66 | 0.17 | 0.14 | 0.22 | 0.12 | 0.15 | 0.02 | −0.01 | −0.01 | 0.00 | 0.04 |
| | (2.77) | (1.21) | (1.03) | (1.63) | (0.88) | (1.06) | (0.13) | (−0.08) | (−0.08) | (−0.04) | (0.26) |
| Meals | 0.67 | 0.15 | 0.07 | 0.14 | 0.08 | 0.11 | −0.24 | −0.23 | −0.24 | −0.10 | −0.24 |
| | (2.42) | (0.81) | (0.41) | (0.82) | (0.45) | (0.62) | (−1.13) | (−1.35) | (−1.35) | (−0.55) | (−1.20) |
| Fin | 0.62 | 0.08 | −0.15 | −0.09 | −0.12 | −0.05 | −0.24 | −0.13 | −0.15 | −0.03 | −0.38 |
| | (2.46) | (0.66) | (−1.54) | (−0.83) | (−1.22) | (−0.47) | (−1.89) | (−1.41) | (−1.26) | (−0.27) | (−3.47) |
| Other | 0.28 | −0.26 | −0.37 | −0.32 | −0.29 | −0.33 | −0.50 | −0.47 | −0.47 | −0.40 | −0.53 |
| | (1.08) | (−2.03) | (−2.66) | (−2.24) | (−2.10) | (−2.43) | (−3.52) | (−3.55) | (−3.48) | (−2.72) | (−3.45) |

Table 1.A11: Average excess returns and alphas of the 8 D10−1 portfolios

The table reports the value-weighted average monthly excess returns and alphas of the 8 D10−1 (high minus low decile) portfolios relative to ten different factor models: the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama and French (1993) three-factor (FF3) model; the Fama and French (1993) and Carhart (1997) four-factor (FFC) model; the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor (FFPS) model; the Asness and Frazzini (2013) three-factor (FFAF) model, which combines their value factor with the market and size factors of the FF3 model; the Hou, Xue, and Zhang (2015) $q$-factor (HXZ) model; the Fama and French (2015) five-factor (FF5) model; the four-factor (FF4) model that excludes the value factor from the FF5 model; the Stambaugh and Yuan (2016) four-factor (SY4) model; and the Barillas and Shanken (2018) six-factor (BS6) model, which includes the market, size, and momentum factors from the FF5 model, the profitability and investment factors from the HXZ model, and the value factor from the FFAF model. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1968 to December 2016.

| | STR | CI | DR | $\beta$ | NI | MAX | RVar | AC |
|---|---|---|---|---|---|---|---|---|
| Average excess returns | −0.32 | −0.24 | 0.17 | −0.06 | −0.66 | −0.51 | −0.77 | −0.43 |
| | (−1.62) | (−1.75) | (0.70) | (−0.21) | (−4.46) | (−1.82) | (−2.43) | (−3.72) |
| CAPM $\alpha$ | −0.13 | −0.22 | −0.06 | −0.56 | −0.79 | −0.93 | −1.21 | −0.47 |
| | (−0.69) | (−1.51) | (−0.27) | (−2.62) | (−5.94) | (−4.43) | (−4.83) | (−4.16) |
| FF3 $\alpha$ | −0.06 | −0.25 | −0.64 | −0.48 | −0.74 | −0.83 | −1.14 | −0.47 |
| | (−0.30) | (−1.87) | (−4.11) | (−2.89) | (−6.33) | (−4.90) | (−6.39) | (−4.10) |
| FFC $\alpha$ | −0.39 | −0.11 | −0.43 | −0.25 | −0.67 | −0.64 | −0.83 | −0.39 |
| | (−1.96) | (−0.77) | (−2.54) | (−1.51) | (−5.70) | (−3.57) | (−4.57) | (−3.42) |
| FFPS $\alpha$ | −0.03 | −0.27 | −0.60 | −0.50 | −0.74 | −0.87 | −1.16 | −0.47 |
| | (−0.13) | (−1.93) | (−4.05) | (−3.00) | (−6.06) | (−5.12) | (−6.49) | (−4.13) |
| FFAF $\alpha$ | 0.05 | −0.28 | −0.47 | −0.61 | −0.79 | −0.99 | −1.33 | −0.48 |
| | (0.26) | (−2.13) | (−2.91) | (−3.36) | (−6.51) | (−5.43) | (−6.60) | (−4.20) |
| HXZ $\alpha$ | −0.31 | −0.15 | −0.28 | 0.01 | −0.46 | −0.20 | −0.25 | −0.43 |
| | (−1.13) | (−0.98) | (−1.40) | (0.05) | (−3.71) | (−1.08) | (−1.34) | (−3.14) |
| FF5 $\alpha$ | −0.15 | −0.28 | −0.43 | −0.18 | −0.45 | −0.35 | −0.56 | −0.50 |
| | (−0.64) | (−2.05) | (−2.77) | (−1.07) | (−4.05) | (−2.41) | (−3.54) | (−3.98) |
| FF4 $\alpha$ | −0.14 | −0.28 | −0.46 | −0.18 | −0.45 | −0.34 | −0.56 | −0.50 |
| | (−0.59) | (−2.03) | (−2.39) | (−1.02) | (−4.02) | (−2.37) | (−3.51) | (−3.99) |
| SY4 $\alpha$ | −0.57 | −0.17 | −0.37 | 0.01 | −0.19 | −0.14 | −0.20 | −0.43 |
| | (−2.66) | (−0.99) | (−1.96) | (0.06) | (−1.75) | (−0.79) | (−0.94) | (−3.39) |
| BS6 $\alpha$ | −0.22 | −0.17 | −0.61 | 0.18 | −0.45 | −0.05 | −0.08 | −0.40 |
| | (−1.06) | (−0.97) | (−2.97) | (0.93) | (−3.44) | (−0.26) | (−0.43) | (−3.01) |

Table 1.A12: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-STR portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.3 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.3 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.577 | −0.582 | −0.622 | −0.487 | −0.510 | −0.627 | −0.573 | −0.553 | −0.660 |
| | (0.046) | (0.062) | (0.132) | (0.021) | (0.128) | (0.098) | (0.049) | (0.066) | (0.023) |
| FF3 | | −0.006 | −0.046 | 0.090 | 0.066 | −0.050 | 0.004 | 0.024 | −0.083 |
| | | (0.649) | (0.155) | (0.195) | (0.138) | (0.311) | (0.909) | (0.372) | (0.105) |
| FFC | | | −0.040 | 0.096 | 0.072 | −0.045 | 0.010 | 0.030 | −0.077 |
| | | | (0.266) | (0.203) | (0.177) | (0.483) | (0.887) | (0.066) | (0.328) |
| FFPS | | | | 0.135 | 0.112 | −0.005 | 0.050 | 0.069 | 0.000 |
| | | | | (0.170) | (0.156) | (0.417) | (0.201) | (0.061) | (0.381) |
| FFAF | | | | | −0.023 | −0.140 | −0.086 | −0.066 | −0.173 |
| | | | | | (0.108) | (0.113) | (0.475) | (0.432) | (0.107) |
| HXZ | | | | | | −0.117 | −0.062 | −0.042 | −0.149 |
| | | | | | | (0.120) | (0.657) | (0.070) | (0.167) |
| FF5 | | | | | | | 0.055 | 0.074 | −0.033 |
| | | | | | | | (0.528) | (0.258) | (0.065) |
| FF4 | | | | | | | | 0.020 | −0.087 |
| | | | | | | | | (0.681) | (0.101) |
| SY4 | | | | | | | | | −0.107 |
| | | | | | | | | | (0.164) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.213 | −0.221 | −0.304 | −0.193 | −0.115 | −0.277 | −0.190 | −0.163 | −0.474 |
| | (0.009) | (0.025) | (0.040) | (0.004) | (0.180) | (0.083) | (0.046) | (0.063) | (0.014) |
| FF3 | | −0.008 | −0.091 | 0.020 | 0.097 | −0.064 | 0.023 | 0.049 | −0.261 |
| | | (0.567) | (0.171) | (0.202) | (0.449) | (0.596) | (0.311) | (0.112) | (0.161) |
| FFC | | | −0.083 | 0.028 | 0.106 | −0.056 | 0.031 | 0.058 | −0.252 |
| | | | (0.333) | (0.164) | (0.454) | (0.710) | (0.415) | (0.182) | (0.051) |
| FFPS | | | | 0.111 | 0.189 | 0.027 | 0.114 | 0.141 | −0.170 |
| | | | | (0.454) | (0.130) | (0.740) | (0.070) | (0.168) | (0.087) |
| FFAF | | | | | 0.078 | −0.084 | 0.003 | 0.030 | −0.280 |
| | | | | | (0.172) | (0.104) | (0.896) | (0.052) | (0.078) |
| HXZ | | | | | | −0.161 | −0.074 | −0.048 | −0.358 |
| | | | | | | (0.162) | (0.087) | (0.300) | (0.095) |
| FF5 | | | | | | | 0.087 | 0.113 | −0.197 |
| | | | | | | | (0.528) | (0.147) | (0.075) |
| FF4 | | | | | | | | 0.026 | −0.284 |
| | | | | | | | | (0.759) | (0.096) |
| SY4 | | | | | | | | | −0.310 |
| | | | | | | | | | (0.129) |

Table 1.A13: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-CI portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.4 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.4 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.352 | −0.482 | −0.365 | −0.301 | −0.403 | −0.352 | −0.352 | −0.442 | −0.486 |
| | (0.023) | (0.150) | (0.036) | (0.034) | (0.048) | (0.043) | (0.036) | (0.052) | (0.141) |
| FF3 | | −0.130 | −0.013 | 0.051 | −0.051 | 0.000 | 0.001 | −0.090 | −0.134 |
| | | (0.035) | (0.398) | (0.116) | (0.122) | (0.745) | (0.149) | (0.225) | (0.151) |
| FFC | | | 0.117 | 0.181 | 0.079 | 0.130 | 0.131 | 0.040 | −0.003 |
| | | | (0.099) | (0.118) | (0.298) | (0.117) | (0.128) | (0.057) | (0.084) |
| FFPS | | | | 0.064 | −0.038 | 0.013 | 0.013 | −0.077 | 0.000 |
| | | | | (0.421) | (0.092) | (0.737) | (0.213) | (0.068) | (0.060) |
| FFAF | | | | | −0.102 | −0.051 | −0.050 | −0.141 | −0.185 |
| | | | | | (0.066) | (0.143) | (0.139) | (0.054) | (0.067) |
| HXZ | | | | | | 0.050 | 0.051 | −0.039 | −0.083 |
| | | | | | | (0.068) | (0.067) | (0.080) | (0.323) |
| FF5 | | | | | | | 0.001 | −0.090 | −0.133 |
| | | | | | | | (0.287) | (0.067) | (0.284) |
| FF4 | | | | | | | | −0.090 | −0.134 |
| | | | | | | | | (0.092) | (0.218) |
| SY4 | | | | | | | | | −0.044 |
| | | | | | | | | | (0.114) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.273 | −0.507 | −0.300 | −0.127 | −0.383 | −0.297 | −0.287 | −0.467 | −0.474 |
| | (0.002) | (0.009) | (0.010) | (0.045) | (0.008) | (0.036) | (0.013) | (0.004) | (0.032) |
| FF3 | | −0.233 | −0.026 | 0.146 | −0.110 | −0.023 | −0.014 | −0.193 | −0.201 |
| | | (0.025) | (0.359) | (0.072) | (0.071) | (0.552) | (0.846) | (0.179) | (0.224) |
| FFC | | | 0.207 | 0.379 | 0.124 | 0.210 | 0.220 | 0.040 | 0.032 |
| | | | (0.054) | (0.076) | (0.425) | (0.109) | (0.150) | (0.160) | (0.051) |
| FFPS | | | | 0.172 | −0.084 | 0.003 | 0.013 | −0.167 | −0.175 |
| | | | | (0.097) | (0.211) | (0.557) | (0.743) | (0.290) | (0.323) |
| FFAF | | | | | −0.256 | −0.169 | −0.160 | −0.339 | −0.347 |
| | | | | | (0.079) | (0.122) | (0.169) | (0.043) | (0.067) |
| HXZ | | | | | | 0.087 | 0.096 | −0.084 | −0.091 |
| | | | | | | (0.063) | (0.054) | (0.191) | (0.129) |
| FF5 | | | | | | | 0.010 | −0.170 | −0.178 |
| | | | | | | | (0.287) | (0.218) | (0.128) |
| FF4 | | | | | | | | −0.180 | −0.187 |
| | | | | | | | | (0.176) | (0.156) |
| SY4 | | | | | | | | | −0.008 |
| | | | | | | | | | (0.749) |

Table 1.A14: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-DR portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.5 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.5 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.217 | −0.297 | −0.219 | −0.251 | −0.246 | −0.252 | −0.187 | −0.270 | −0.298 |
| | (0.495) | (0.561) | (0.573) | (0.454) | (0.536) | (0.611) | (0.658) | (0.513) | (0.712) |
| FF3 | | −0.081 | −0.002 | −0.034 | −0.029 | −0.035 | 0.029 | −0.053 | −0.081 |
| | | (0.235) | (0.831) | (0.342) | (0.810) | (0.940) | (0.874) | (0.767) | (0.851) |
| FFC | | | 0.078 | 0.047 | 0.051 | 0.045 | 0.110 | 0.027 | −0.001 |
| | | | (0.400) | (0.443) | (0.830) | (0.815) | (0.821) | (0.789) | (1.000) |
| FFPS | | | | −0.032 | −0.027 | −0.033 | 0.032 | −0.051 | 0.000 |
| | | | | (0.528) | (0.885) | (0.976) | (0.932) | (0.830) | (0.855) |
| FFAF | | | | | 0.005 | −0.001 | 0.063 | −0.019 | −0.048 |
| | | | | | (0.743) | (0.776) | (0.727) | (0.739) | (0.954) |
| HXZ | | | | | | −0.006 | 0.059 | −0.024 | −0.052 |
| | | | | | | (0.813) | (0.807) | (0.864) | (0.750) |
| FF5 | | | | | | | 0.065 | −0.018 | −0.046 |
| | | | | | | | (0.413) | (0.894) | (0.820) |
| FF4 | | | | | | | | −0.083 | −0.111 |
| | | | | | | | | (0.843) | (0.805) |
| SY4 | | | | | | | | | −0.028 |
| | | | | | | | | | (0.897) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.086 | −0.242 | −0.088 | −0.133 | −0.148 | −0.102 | −0.058 | −0.149 | −0.256 |
| | (0.431) | (0.362) | (0.650) | (0.278) | (0.452) | (0.779) | (0.800) | (0.430) | (0.632) |
| FF3 | | −0.156 | −0.002 | −0.047 | −0.062 | −0.016 | 0.028 | −0.063 | −0.170 |
| | | (0.191) | (0.861) | (0.279) | (0.754) | (0.969) | (0.858) | (0.743) | (0.773) |
| FFC | | | 0.154 | 0.109 | 0.094 | 0.140 | 0.184 | 0.093 | −0.014 |
| | | | (0.402) | (0.371) | (0.701) | (0.826) | (0.743) | (0.733) | (0.998) |
| FFPS | | | | −0.045 | −0.060 | −0.015 | 0.029 | −0.062 | −0.169 |
| | | | | (0.435) | (0.832) | (0.990) | (0.920) | (0.831) | (0.841) |
| FFAF | | | | | −0.015 | 0.030 | 0.074 | −0.017 | −0.124 |
| | | | | | (0.710) | (0.748) | (0.662) | (0.660) | (0.896) |
| HXZ | | | | | | 0.046 | 0.090 | −0.001 | −0.108 |
| | | | | | | (0.782) | (0.600) | (0.785) | (0.665) |
| FF5 | | | | | | | 0.044 | −0.047 | −0.154 |
| | | | | | | | (0.413) | (0.858) | (0.750) |
| FF4 | | | | | | | | −0.091 | −0.198 |
| | | | | | | | | (0.785) | (0.776) |
| SY4 | | | | | | | | | −0.107 |
| | | | | | | | | | (0.841) |

Table 1.A15: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-$\beta$ portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.6 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.6 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.693 | −0.785 | −0.710 | −0.554 | −0.743 | −0.749 | −0.745 | −0.750 | −0.778 |
| | (0.071) | (0.099) | (0.096) | (0.113) | (0.039) | (0.044) | (0.034) | (0.045) | (0.072) |
| FF3 | | −0.091 | −0.016 | 0.139 | −0.050 | −0.056 | −0.052 | −0.057 | −0.084 |
| | | (0.063) | (0.321) | (0.200) | (0.599) | (0.480) | (0.693) | (0.378) | (0.090) |
| FFC | | | 0.075 | 0.231 | 0.041 | 0.035 | 0.040 | 0.034 | 0.007 |
| | | | (0.149) | (0.080) | (0.070) | (0.417) | (0.074) | (0.102) | (0.224) |
| FFPS | | | | 0.156 | −0.034 | −0.039 | −0.035 | −0.041 | 0.000 |
| | | | | (0.103) | (0.098) | (0.630) | (0.101) | (0.089) | (0.150) |
| FFAF | | | | | −0.189 | −0.195 | −0.191 | −0.196 | −0.224 |
| | | | | | (0.058) | (0.100) | (0.060) | (0.053) | (0.224) |
| HXZ | | | | | | −0.006 | −0.001 | −0.007 | −0.034 |
| | | | | | | (0.145) | (0.097) | (0.067) | (0.204) |
| FF5 | | | | | | | 0.004 | −0.001 | −0.028 |
| | | | | | | | (0.965) | (0.092) | (0.342) |
| FF4 | | | | | | | | −0.006 | −0.033 |
| | | | | | | | | (0.075) | (0.264) |
| SY4 | | | | | | | | | −0.027 |
| | | | | | | | | | (0.199) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.218 | −0.443 | −0.246 | −0.070 | −0.337 | −0.325 | −0.323 | −0.429 | −0.448 |
| | (0.021) | (0.029) | (0.047) | (0.347) | (0.013) | (0.028) | (0.013) | (0.009) | (0.051) |
| FF3 | | −0.225 | −0.028 | 0.148 | −0.119 | −0.107 | −0.105 | −0.212 | −0.230 |
| | | (0.051) | (0.365) | (0.175) | (0.184) | (0.267) | (0.256) | (0.249) | (0.255) |
| FFC | | | 0.198 | 0.373 | 0.106 | 0.118 | 0.120 | 0.014 | −0.004 |
| | | | (0.116) | (0.097) | (0.537) | (0.155) | (0.542) | (0.229) | (0.124) |
| FFPS | | | | 0.175 | −0.091 | −0.079 | −0.077 | −0.184 | −0.202 |
| | | | | (0.078) | (0.306) | (0.371) | (0.468) | (0.053) | (0.077) |
| FFAF | | | | | −0.267 | −0.255 | −0.253 | −0.359 | −0.377 |
| | | | | | (0.100) | (0.089) | (0.091) | (0.054) | (0.071) |
| HXZ | | | | | | 0.012 | 0.014 | −0.093 | −0.111 |
| | | | | | | (0.413) | (0.522) | (0.141) | (0.085) |
| FF5 | | | | | | | 0.002 | −0.105 | −0.123 |
| | | | | | | | (0.965) | (0.450) | (0.165) |
| FF4 | | | | | | | | −0.107 | −0.125 |
| | | | | | | | | (0.063) | (0.109) |
| SY4 | | | | | | | | | −0.018 |
| | | | | | | | | | (0.061) |

Table 1.A16: (Sequential) Tests of equality of cross-sectional $R^2$s: 35 size-NI portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.7 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.7 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.438 | −0.641 | −0.463 | −0.315 | −0.645 | −0.607 | −0.596 | −0.660 | −0.665 |
| | (0.006) | (0.055) | (0.016) | (0.017) | (0.004) | (0.004) | (0.005) | (0.003) | (0.020) |
| FF3 | | −0.203 | −0.025 | 0.124 | −0.206 | −0.169 | −0.158 | −0.222 | −0.227 |
| | | (0.009) | (0.349) | (0.047) | (0.011) | (0.025) | (0.031) | (0.015) | (0.020) |
| FFC | | | 0.178 | 0.326 | −0.004 | 0.034 | 0.045 | −0.019 | −0.024 |
| | | | (0.070) | (0.010) | (0.136) | (0.734) | (0.677) | (0.138) | (0.229) |
| FFPS | | | | 0.148 | −0.182 | −0.144 | −0.133 | −0.197 | 0.001 |
| | | | | (0.064) | (0.052) | (0.109) | (0.134) | (0.045) | (0.037) |
| FFAF | | | | | −0.330 | −0.292 | −0.282 | −0.345 | −0.350 |
| | | | | | (0.004) | (0.008) | (0.013) | (0.003) | (0.004) |
| HXZ | | | | | | 0.038 | 0.048 | −0.015 | −0.020 |
| | | | | | | (0.434) | (0.056) | (0.745) | (0.241) |
| FF5 | | | | | | | 0.011 | −0.053 | −0.058 |
| | | | | | | | (0.365) | (0.404) | (0.416) |
| FF4 | | | | | | | | −0.064 | −0.069 |
| | | | | | | | | (0.067) | (0.051) |
| SY4 | | | | | | | | | −0.005 |
| | | | | | | | | | (0.439) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.094 | −0.278 | −0.101 | −0.029 | −0.307 | −0.226 | −0.223 | −0.336 | −0.329 |
| | (0.007) | (0.013) | (0.108) | (0.207) | (0.000) | (0.004) | (0.001) | (0.000) | (0.016) |
| FF3 | | −0.184 | −0.008 | 0.065 | −0.214 | −0.132 | −0.130 | −0.242 | −0.235 |
| | | (0.019) | (0.605) | (0.128) | (0.023) | (0.075) | (0.068) | (0.018) | (0.053) |
| FFC | | | 0.177 | 0.249 | −0.029 | 0.052 | 0.055 | −0.058 | −0.051 |
| | | | (0.065) | (0.081) | (0.498) | (0.702) | (0.689) | (0.543) | (0.831) |
| FFPS | | | | 0.072 | −0.206 | −0.125 | −0.122 | −0.235 | −0.227 |
| | | | | (0.155) | (0.041) | (0.132) | (0.127) | (0.027) | (0.066) |
| FFAF | | | | | −0.278 | −0.197 | −0.194 | −0.307 | −0.300 |
| | | | | | (0.006) | (0.014) | (0.017) | (0.003) | (0.018) |
| HXZ | | | | | | 0.081 | 0.084 | −0.029 | −0.021 |
| | | | | | | (0.229) | (0.223) | (0.815) | (0.325) |
| FF5 | | | | | | | 0.003 | −0.110 | −0.103 |
| | | | | | | | (0.365) | (0.180) | (0.329) |
| FF4 | | | | | | | | −0.113 | −0.105 |
| | | | | | | | | (0.196) | (0.333) |
| SY4 | | | | | | | | | 0.007 |
| | | | | | | | | | (0.563) |

Table 1.A17: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-MAX portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.8 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.8 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.313 | −0.383 | −0.315 | −0.212 | −0.345 | −0.366 | −0.354 | −0.359 | −0.393 |
| | (0.007) | (0.039) | (0.011) | (0.023) | (0.009) | (0.056) | (0.012) | (0.007) | (0.034) |
| FF3 | | −0.069 | −0.002 | 0.101 | −0.032 | −0.052 | −0.041 | −0.046 | −0.080 |
| | | (0.091) | (0.691) | (0.108) | (0.147) | (0.376) | (0.124) | (0.301) | (0.231) |
| FFC | | | 0.067 | 0.170 | 0.037 | 0.017 | 0.028 | 0.023 | −0.011 |
| | | | (0.242) | (0.061) | (0.458) | (0.206) | (0.051) | (0.554) | (0.062) |
| FFPS | | | | 0.103 | −0.030 | −0.050 | −0.039 | −0.044 | 0.001 |
| | | | | (0.088) | (0.124) | (0.454) | (0.097) | (0.342) | (0.238) |
| FFAF | | | | | −0.133 | −0.153 | −0.142 | −0.147 | −0.181 |
| | | | | | (0.123) | (0.051) | (0.080) | (0.081) | (0.072) |
| HXZ | | | | | | −0.020 | −0.009 | −0.014 | −0.048 |
| | | | | | | (0.293) | (0.535) | (0.200) | (0.369) |
| FF5 | | | | | | | 0.011 | 0.007 | −0.028 |
| | | | | | | | (0.824) | (0.756) | (0.185) |
| FF4 | | | | | | | | −0.005 | −0.039 |
| | | | | | | | | (0.668) | (0.067) |
| SY4 | | | | | | | | | −0.034 |
| | | | | | | | | | (0.145) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.107 | −0.219 | −0.110 | −0.024 | −0.229 | −0.245 | −0.238 | −0.293 | −0.263 |
| | (0.003) | (0.032) | (0.040) | (0.371) | (0.004) | (0.058) | (0.015) | (0.002) | (0.169) |
| FF3 | | −0.113 | −0.003 | 0.082 | −0.122 | −0.138 | −0.132 | −0.186 | −0.156 |
| | | (0.092) | (0.682) | (0.093) | (0.243) | (0.167) | (0.145) | (0.053) | (0.121) |
| FFC | | | 0.109 | 0.195 | −0.009 | −0.025 | −0.019 | −0.074 | −0.044 |
| | | | (0.243) | (0.157) | (0.327) | (0.070) | (0.425) | (0.476) | (0.647) |
| FFPS | | | | 0.086 | −0.119 | −0.135 | −0.128 | −0.183 | −0.153 |
| | | | | (0.110) | (0.251) | (0.080) | (0.148) | (0.058) | (0.126) |
| FFAF | | | | | −0.205 | −0.221 | −0.214 | −0.269 | −0.239 |
| | | | | | (0.048) | (0.015) | (0.010) | (0.016) | (0.017) |
| HXZ | | | | | | −0.016 | −0.010 | −0.064 | −0.034 |
| | | | | | | (0.965) | (0.917) | (0.474) | (0.376) |
| FF5 | | | | | | | 0.007 | −0.048 | −0.018 |
| | | | | | | | (0.824) | (0.607) | (0.427) |
| FF4 | | | | | | | | −0.055 | −0.025 |
| | | | | | | | | (0.594) | (0.392) |
| SY4 | | | | | | | | | 0.030 |
| | | | | | | | | | (0.133) |

Table 1.A18: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-RVar portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.9 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.9 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.296 | −0.481 | −0.314 | −0.096 | −0.542 | −0.580 | −0.580 | −0.520 | −0.579 |
| | (0.006) | (0.071) | (0.019) | (0.162) | (0.002) | (0.017) | (0.008) | (0.013) | (0.013) |
| FF3 | | −0.185 | −0.018 | 0.200 | −0.246 | −0.285 | −0.284 | −0.224 | −0.283 |
| | | (0.048) | (0.409) | (0.069) | (0.034) | (0.012) | (0.011) | (0.054) | (0.010) |
| FFC | | | 0.167 | 0.385 | −0.061 | −0.099 | −0.099 | −0.039 | −0.098 |
| | | | (0.087) | (0.062) | (0.363) | (0.117) | (0.118) | (0.440) | (0.116) |
| FFPS | | | | 0.218 | −0.228 | −0.267 | −0.266 | −0.206 | 0.003 |
| | | | | (0.089) | (0.061) | (0.024) | (0.023) | (0.094) | (0.017) |
| FFAF | | | | | −0.446 | −0.485 | −0.484 | −0.424 | −0.483 |
| | | | | | (0.006) | (0.003) | (0.003) | (0.011) | (0.004) |
| HXZ | | | | | | −0.039 | −0.038 | 0.022 | −0.037 |
| | | | | | | (0.388) | (0.360) | (0.458) | (0.341) |
| FF5 | | | | | | | 0.001 | 0.060 | 0.002 |
| | | | | | | | (0.360) | (0.207) | (0.061) |
| FF4 | | | | | | | | 0.060 | 0.001 |
| | | | | | | | | (0.180) | (0.952) |
| SY4 | | | | | | | | | −0.059 |
| | | | | | | | | | (0.055) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.028 | −0.051 | −0.030 | −0.006 | −0.266 | −0.450 | −0.449 | −0.170 | −0.392 |
| | (0.220) | (0.400) | (0.495) | (0.778) | (0.001) | (0.006) | (0.001) | (0.040) | (0.013) |
| FF3 | | −0.023 | −0.003 | 0.021 | −0.238 | −0.422 | −0.422 | −0.143 | −0.364 |
| | | (0.431) | (0.725) | (0.248) | (0.069) | (0.012) | (0.010) | (0.056) | (0.019) |
| FFC | | | 0.020 | 0.045 | −0.215 | −0.399 | −0.398 | −0.119 | −0.341 |
| | | | (0.704) | (0.346) | (0.051) | (0.016) | (0.015) | (0.228) | (0.037) |
| FFPS | | | | 0.024 | −0.235 | −0.420 | −0.419 | −0.140 | −0.361 |
| | | | | (0.380) | (0.075) | (0.011) | (0.010) | (0.088) | (0.021) |
| FFAF | | | | | −0.259 | −0.444 | −0.443 | −0.164 | −0.386 |
| | | | | | (0.035) | (0.007) | (0.006) | (0.055) | (0.012) |
| HXZ | | | | | | −0.184 | −0.184 | 0.095 | −0.126 |
| | | | | | | (0.137) | (0.127) | (0.190) | (0.250) |
| FF5 | | | | | | | 0.001 | 0.280 | 0.058 |
| | | | | | | | (0.360) | (0.035) | (0.283) |
| FF4 | | | | | | | | 0.279 | 0.057 |
| | | | | | | | | (0.031) | (0.247) |
| SY4 | | | | | | | | | −0.222 |
| | | | | | | | | | (0.131) |

Table 1.A19: (Sequential) Tests of equality of cross-sectional $R^2$s: 25 size-AC portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.10 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.10 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.360 | −0.639 | −0.382 | −0.335 | −0.494 | −0.584 | −0.551 | −0.489 | −0.680 |
| | (0.093) | (0.201) | (0.144) | (0.121) | (0.079) | (0.048) | (0.025) | (0.106) | (0.202) |
| FF3 | | −0.279 | −0.022 | 0.025 | −0.134 | −0.224 | −0.191 | −0.129 | −0.320 |
| | | (0.007) | (0.568) | (0.280) | (0.092) | (0.056) | (0.099) | (0.070) | (0.083) |
| FFC | | | 0.257 | 0.304 | 0.145 | 0.055 | 0.088 | 0.150 | −0.041 |
| | | | (0.185) | (0.143) | (0.420) | (0.717) | (0.556) | (0.412) | (0.144) |
| FFPS | | | | 0.047 | −0.112 | −0.202 | −0.169 | −0.107 | 0.001 |
| | | | | (0.349) | (0.067) | (0.095) | (0.203) | (0.129) | (0.098) |
| FFAF | | | | | −0.159 | −0.249 | −0.216 | −0.154 | −0.345 |
| | | | | | (0.083) | (0.080) | (0.078) | (0.076) | (0.081) |
| HXZ | | | | | | −0.090 | −0.057 | 0.005 | −0.186 |
| | | | | | | (0.393) | (0.111) | (0.640) | (0.176) |
| FF5 | | | | | | | 0.033 | 0.095 | −0.096 |
| | | | | | | | (0.507) | (0.246) | (0.466) |
| FF4 | | | | | | | | 0.062 | −0.129 |
| | | | | | | | | (0.525) | (0.324) |
| SY4 | | | | | | | | | −0.191 |
| | | | | | | | | | (0.275) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.080 | −0.301 | −0.106 | −0.077 | −0.140 | −0.212 | −0.158 | −0.174 | −0.352 |
| | (0.103) | (0.066) | (0.328) | (0.158) | (0.092) | (0.059) | (0.033) | (0.092) | (0.111) |
| FF3 | | −0.222 | −0.026 | 0.003 | −0.061 | −0.132 | −0.078 | −0.095 | −0.272 |
| | | (0.054) | (0.510) | (0.691) | (0.063) | (0.235) | (0.077) | (0.087) | (0.145) |
| FFC | | | 0.196 | 0.225 | 0.161 | 0.089 | 0.144 | 0.127 | −0.050 |
| | | | (0.135) | (0.288) | (0.410) | (0.658) | (0.468) | (0.069) | (0.194) |
| FFPS | | | | 0.029 | −0.035 | −0.106 | −0.052 | −0.068 | −0.246 |
| | | | | (0.713) | (0.117) | (0.094) | (0.057) | (0.172) | (0.103) |
| FFAF | | | | | −0.064 | −0.135 | −0.081 | −0.097 | −0.275 |
| | | | | | (0.165) | (0.241) | (0.097) | (0.066) | (0.142) |
| HXZ | | | | | | −0.072 | −0.017 | −0.034 | −0.211 |
| | | | | | | (0.177) | (0.811) | (0.090) | (0.083) |
| FF5 | | | | | | | 0.055 | 0.038 | −0.140 |
| | | | | | | | (0.507) | (0.642) | (0.179) |
| FF4 | | | | | | | | −0.017 | −0.194 |
| | | | | | | | | (0.485) | (0.135) |
| SY4 | | | | | | | | | −0.178 |
| | | | | | | | | | (0.064) |

Table 1.A20: (Sequential) Tests of equality of cross-sectional $R^2$s: 30 IND portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.11 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.11 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.044 | −0.046 | −0.045 | −0.046 | −0.168 | −0.280 | −0.206 | −0.210 | −0.183 |
| | (0.782) | (0.936) | (0.941) | (0.773) | (0.644) | (0.645) | (0.635) | (0.550) | (0.907) |
| FF3 | | −0.001 | −0.001 | −0.001 | −0.123 | −0.235 | −0.162 | −0.166 | −0.139 |
| | | (0.927) | (0.953) | (0.926) | (0.881) | (0.461) | (0.791) | (0.764) | (0.967) |
| FFC | | | 0.001 | 0.000 | −0.122 | −0.234 | −0.161 | −0.164 | −0.138 |
| | | | (0.996) | (0.983) | (0.940) | (0.596) | (0.869) | (0.858) | (0.948) |
| FFPS | | | | −0.001 | −0.123 | −0.235 | −0.161 | −0.165 | 0.000 |
| | | | | (0.985) | (0.886) | (0.564) | (0.787) | (0.793) | (0.958) |
| FFAF | | | | | −0.122 | −0.234 | −0.161 | −0.164 | −0.138 |
| | | | | | (0.916) | (0.687) | (0.881) | (0.688) | (0.927) |
| HXZ | | | | | | −0.112 | −0.039 | −0.042 | −0.016 |
| | | | | | | (0.818) | (0.946) | (0.850) | (0.998) |
| FF5 | | | | | | | 0.073 | 0.070 | 0.096 |
| | | | | | | | (0.805) | (0.825) | (0.705) |
| FF4 | | | | | | | | −0.004 | 0.023 |
| | | | | | | | | (0.861) | (0.921) |
| SY4 | | | | | | | | | 0.027 |
| | | | | | | | | | (0.937) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.087 | −0.102 | −0.087 | −0.080 | −0.113 | −0.164 | −0.161 | −0.104 | −0.170 |
| | (0.381) | (0.520) | (0.591) | (0.404) | (0.498) | (0.518) | (0.361) | (0.562) | (0.671) |
| FF3 | | −0.015 | 0.000 | 0.007 | −0.027 | −0.077 | −0.074 | −0.017 | −0.083 |
| | | (0.574) | (0.967) | (0.833) | (0.753) | (0.481) | (0.623) | (0.759) | (0.776) |
| FFC | | | 0.015 | 0.022 | −0.012 | −0.062 | −0.059 | −0.002 | −0.068 |
| | | | (0.846) | (0.924) | (0.695) | (0.498) | (0.624) | (0.727) | (0.632) |
| FFPS | | | | 0.007 | −0.026 | −0.077 | −0.074 | −0.017 | −0.083 |
| | | | | (0.940) | (0.843) | (0.623) | (0.741) | (0.854) | (0.853) |
| FFAF | | | | | −0.033 | −0.084 | −0.081 | −0.024 | −0.090 |
| | | | | | (0.659) | (0.630) | (0.664) | (0.702) | (0.613) |
| HXZ | | | | | | −0.051 | −0.048 | 0.009 | −0.057 |
| | | | | | | (0.843) | (0.783) | (0.869) | (0.738) |
| FF5 | | | | | | | 0.003 | 0.060 | −0.006 |
| | | | | | | | (0.805) | (0.824) | (0.845) |
| FF4 | | | | | | | | 0.057 | −0.009 |
| | | | | | | | | (0.792) | (0.858) |
| SY4 | | | | | | | | | −0.066 |
| | | | | | | | | | (0.877) |

Table 1.A21: (Sequential) Tests of equality of cross-sectional $R^2$s: 8 D10−1 portfolios

The table reports pairwise tests of equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.12 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.12 in the main chapter.

| Panel A: OLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.690 | −0.861 | −0.832 | −0.543 | −0.889 | −0.914 | −0.817 | −0.972 | −0.986 |
| | (0.026) | (0.035) | (0.291) | (0.051) | (0.011) | (0.009) | (0.008) | (0.007) | (0.039) |
| FF3 | | −0.171 | −0.142 | 0.147 | −0.199 | −0.224 | −0.127 | −0.281 | −0.296 |
| | | (0.071) | (0.198) | (0.065) | (0.096) | (0.054) | (0.052) | (0.195) | (0.056) |
| FFC | | | 0.029 | 0.318 | −0.028 | −0.053 | 0.043 | −0.111 | −0.126 |
| | | | (0.175) | (0.111) | (0.573) | (0.670) | (0.466) | (0.133) | (0.362) |
| FFPS | | | | 0.289 | −0.057 | −0.082 | 0.014 | −0.140 | 0.017 |
| | | | | (0.192) | (0.067) | (0.973) | (0.376) | (0.632) | (0.801) |
| FFAF | | | | | −0.346 | −0.371 | −0.275 | −0.429 | −0.444 |
| | | | | | (0.066) | (0.099) | (0.125) | (0.112) | (0.111) |
| HXZ | | | | | | −0.025 | 0.071 | −0.083 | −0.098 |
| | | | | | | (0.979) | (0.071) | (0.396) | (0.743) |
| FF5 | | | | | | | 0.097 | −0.058 | −0.072 |
| | | | | | | | (0.412) | (0.272) | (0.406) |
| FF4 | | | | | | | | −0.154 | −0.169 |
| | | | | | | | | (0.100) | (0.183) |
| SY4 | | | | | | | | | −0.015 |
| | | | | | | | | | (0.596) |

| Panel B: GLS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | FF3 | FFC | FFPS | FFAF | HXZ | FF5 | FF4 | SY4 | BS6 |
| CAPM | −0.607 | −0.669 | −0.687 | −0.461 | −0.797 | −0.823 | −0.782 | −0.883 | −0.913 |
| | (0.005) | (0.010) | (0.111) | (0.016) | (0.001) | (0.002) | (0.001) | (0.000) | (0.014) |
| FF3 | | −0.062 | −0.080 | 0.146 | −0.191 | −0.216 | −0.175 | −0.276 | −0.306 |
| | | (0.310) | (0.389) | (0.181) | (0.070) | (0.129) | (0.082) | (0.197) | (0.110) |
| FFC | | | −0.018 | 0.207 | −0.129 | −0.154 | −0.114 | −0.214 | −0.244 |
| | | | (0.535) | (0.153) | (0.091) | (0.233) | (0.192) | (0.272) | (0.112) |
| FFPS | | | | 0.226 | −0.110 | −0.136 | −0.095 | −0.196 | −0.226 |
| | | | | (0.209) | (0.556) | (0.054) | (0.701) | (0.349) | (0.462) |
| FFAF | | | | | −0.336 | −0.361 | −0.321 | −0.422 | −0.452 |
| | | | | | (0.134) | (0.110) | (0.103) | (0.112) | (0.105) |
| HXZ | | | | | | −0.025 | 0.015 | −0.085 | −0.116 |
| | | | | | | (0.903) | (0.588) | (0.398) | (0.733) |
| FF5 | | | | | | | 0.040 | −0.060 | −0.090 |
| | | | | | | | (0.412) | (0.292) | (0.379) |
| FF4 | | | | | | | | −0.101 | −0.131 |
| | | | | | | | | (0.224) | (0.424) |
| SY4 | | | | | | | | | −0.030 |
| | | | | | | | | | (0.778) |

Table 1.A22: Summary of factor model performance: (Sequential) Tests of equality of cross-sectional $R^2$s

The table reports summary of pairwise tests for equality of the ordinary least squares (OLS) and generalized least squares (GLS) cross-sectional regression $R^2$s for ten different factor models. The setup is the same as in Table 1.13 of the main chapter except that the test of $H_0$: $\rho_i^2 = \rho_j^2$ for nonnested models entails a sequential test. The sample period is from January 1968 to December 2016. See also notes to Table 1.13 in the main chapter.

| Panel A: OLS | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Size-STR | Size-CI | Size-DR | Size-$\beta$ | Size-NI | Size-MAX | Size-RVar | Size-AC | IND | D10−1 |
| CAPM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| FF3 | 1 | 1 | 0 | 0 | 2 | 1 | 1 | 0 | 0 | 1 |
| FFC | 0 | 1 | 0 | 0 | 2 | 1 | 1 | 1 | 0 | 1 |
| FFPS | 0 | 1 | 0 | 0 | 2 | 1 | 2 | 0 | 0 | 0 |
| FFAF | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| HXZ | 0 | 1 | 0 | 1 | 3 | 1 | 3 | 0 | 0 | 1 |
| FF5 | 0 | 1 | 0 | 1 | 3 | 0 | 4 | 1 | 0 | 1 |
| FF4 | 1 | 1 | 0 | 1 | 3 | 1 | 4 | 1 | 0 | 1 |
| SY4 | 0 | 0 | 0 | 1 | 4 | 1 | 2 | 0 | 0 | 1 |
| BS6 | 1 | 0 | 0 | 0 | 3 | 1 | 3 | 0 | 0 | 1 |
| Panel B: GLS | | | | | | | | | | |
| CAPM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| FF3 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| FFC | 1 | 2 | 0 | 1 | 2 | 1 | 0 | 0 | 0 | 1 |
| FFPS | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| FFAF | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| HXZ | 0 | 1 | 0 | 1 | 4 | 2 | 2 | 0 | 0 | 1 |
| FF5 | 0 | 1 | 0 | 1 | 2 | 1 | 6 | 0 | 0 | 1 |
| FF4 | 1 | 1 | 0 | 1 | 2 | 2 | 6 | 1 | 0 | 1 |
| SY4 | 0 | 2 | 0 | 1 | 4 | 2 | 1 | 0 | 0 | 1 |
| BS6 | 1 | 1 | 0 | 0 | 2 | 1 | 5 | 0 | 0 | 1 |

# Chapter 2

# Illiquidity, R&D investment, and the cross-section of stock returns

## 2.1 Introduction

Investment in research and development (R&D) plays a critical role in improving firms' productivity, and thereby promoting a nation's economic growth (Hall, 1996). Over the years, firms in the United States have invested heavily in R&D activities. For example, according to the National Science Foundation's data, privately funded industrial R&D increased to $356 billion in 2015, from $247 billion in 2009. Despite its growing importance, to date only a small number of studies (see Cohen, Diether, and Malloy, 2013; Gu, 2016; Li, 2011) have investigated the factors that potentially affect the relation between R&D investment and future stock returns.

This chapter contributes to such exploratory investigation by developing a simple model of R&D venture, which offers a substantive insight into the R&D-return relation from the perspective of stock illiquidity. In my model, the firm conducting an R&D project generates a stochastic payoff after it successfully completes a number of sequential steps. The probability of success depends partly on the resources and efforts spent on the project and partly on experience or expertise gathered by the firm while traversing the time path of the project. During the course of the project, the firm faces the following trade-offs in allocating resources over time. On the one hand, if the firm currently spends a large amount of its resources to the R&D project, then it progresses faster along the steps towards its fruition and if successful, then the discounted value of the payoff from the R&D venture is larger. On the other hand, completing the project too early increases the probability of failure at an early stage because insufficient experience or knowledge is gathered by the firm over the shorter duration of the project. In addition, early completion of the R&D project increases expenses at the margin, since discounting of cash outflows renders costs incurred at a future date lower than costs

incurred earlier.

In this environment, a firm that lacks sufficient internal funds to cover its R&D expenses but which anyway wishes to continue the project issues outside financial claims (i.e., new public shares) at the beginning of the project to investors who may face liquidity problems at a later date before completion of the project.[1] This implies that liquidity constrained investors may have to sell their stocks before they receive any payoff from the successful completion of the project. If the financial market is perfectly liquid and investors can sell their stocks instantaneously, then the problem is unlikely to arise. However, in the presence of asymmetric information due to the relatively unique nature of R&D activities (see, among others, Aboody and Lev, 2000), investors or dealers who are willing to buy such stocks may find it difficult to decipher whether this sale is triggered by a liquidity trader or by an informed trader selling upon receiving bad news (e.g., a failure of a drug under development to pass Phase I clinical tests).[2] This translates into an illiquidity-induced increase in the R&D premium to outside investors, which in turn forces the firm to expedite project completion because of increased costs (i.e., due to illiquidity) associated with external equity financing. Moreover, this illiquidity-induced reduction of time for project completion increases the likelihood of its failure. As a result, the risk of R&D-intensive firm increases with stock illiquidity. To formalize this intuition and to motivate empirical analyses, I develop a new testable hypothesis, based on my theoretical model (see Section 2.2), that the positive relation between a firm's R&D investment and expected stock returns strengthens with the level of illiquidity.

I test my hypothesis both by Fama and MacBeth (1973) cross-sectional regressions and by independently double sorting stocks on illiquidity and R&D intensity. The cross-sectional regressions, which also control for the potential effects of size, book-to-market equity, short-term reversal, and momentum, confirm that the positive R&D-return relation is much stronger among illiquid stocks. For example, when R&D-to-market (i.e., R&D expenditure scaled by market value of equity) and bid-ask spread are used, respectively, as measures of a firm's R&D intensity and stock illiquidity, the average coefficient estimates on R&D-to-market are 5.69 ($t$-statistic = 6.67) and 0.95 ($t$-statistic = 1.31), respectively, for

[1] Brown, Fazzari, and Petersen (2009) and Carpenter and Petersen (2002) suggest that for R&D-intensive firms, especially young ones, in the United States, there exists a financing hierarchy, which consists almost entirely of internal and external equity finance. Along this line of evidence, Hall (2002) concludes that debt is a disfavored source of finance for R&D investment.

[2] The inference problem mainly originates from: (1) the existence of different types of firm with varying abilities to succeed in R&D projects; and (2) an informed insider who has this information at the time of sale. Neither market maker nor liquidity trader observes either cause of selling. For an elaboration of this problem, see Glosten and Milgrom (1985).

high and low illiquid stocks. Importantly, the average spread between the estimated slope coefficients on R&D-to-market for high and low illiquid stocks is 4.74, which is statistically significant with a $t$-statistic of 6.00. The results remain qualitatively similar, when I conduct cross-sectional regression analyses using: the all-but-microcaps sample, which excludes stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution; industry dummies as additional control variables; subperiods; stock returns adjusted for delistings, following Shumway (1997); samples partitioned into high-tech firms and low-tech firms; alternative versions of the bid-ask spread; R&D intensity measured by R&D-to-total assets (i.e., R&D expenditure scaled by total assets); and the Amihud (2002) illiquidity measure. In a separate cross-sectional regression analysis, I also create interaction terms involving illiquidity dummy variables. After controlling for firm-level attributes, such as size, book-to-market equity, short-term reversal, and momentum, the results remain robust and support my theoretical model's prediction of a stronger R&D-return relation among illiquid stocks. For example, I find that, all else being equal, a one-standard deviation increase in R&D-to-market ratio is associated with a 39 basis point higher future return per month for high illiquid stocks relative to all other stocks.

The model's prediction is also empirically supported by the results from an independent double-sorted portfolio analysis. Similar to the results from the Fama and MacBeth (1973) cross-sectional regressions, the positive R&D-return relation strengthens with the level of stock illiquidity. For example, among stocks with high illiquidity, the high-minus-low R&D-to-market portfolio delivers a value-weighted average monthly return of 1.57% ($t$-statistic = 4.79). The R&D premium among illiquid stocks persists even after adjusting for risk using empirical factor pricing models. The value-weighted average monthly abnormal returns on the spread portfolio relative to the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model are 1.59%, 1.36%, and 1.47%, respectively, with $t$-statistics of 4.85, 3.50, and 4.65. In contrast, among stocks with low illiquidity, the high-minus-low R&D-to-market portfolio generates an insignificantly lower monthly return of 0.08% ($t$-statistic = 0.51). Moreover, the average monthly abnormal returns on the portfolio relative to the three asset pricing models are much lower and statistically indistinguishable from zero at conventional levels. Specifically, the three-factor, the four-factor, and the five-factor model alphas are, respectively, −0.18% ($t$-statistic = −1.07), −0.08% ($t$-statistic = −0.46), and −0.12% ($t$-statistic = −0.72). The empirical results, supporting my hypothesis, remain robust to using the all-but-microcaps sample, alternative measures of a firm's R&D intensity and stock

illiquidity, and double-sorted quartile or quintile portfolios.

My paper complements and extends a growing body of literature on the relation between R&D investment and subsequent stock returns (see, among others, Chambers, Jennings, and Thompson, 2002; Chan, Martin, and Kensinger, 1990; Chan, Lakonishok, and Sougiannis, 2001; Eberhart, Maxwell, and Siddique, 2004; Hirshleifer, Hsu, and Li, 2013, 2018; Kumar and Li, 2016; Lev and Sougiannis, 1996; Lin, 2012; Penman and Zhang, 2002). To the best of my knowledge, I are the first to theoretically illustrate and empirically show that the positive R&D-return relation increases with the level of stock illiquidity. Some recent studies demonstrate that financial constraints (see Li, 2011), innovation ability (see Cohen, Diether, and Malloy, 2013), and product market competition (see Gu, 2016) affect the R&D premium in the cross-section of stocks. In fact, both Li (2011) and Gu (2016) develop real option models, which, respectively, predict that the positive R&D-return relation increases with the financial constraints and the product market competition. My model differs from theirs in that its mechanism is based on a firm's stock illiquidity emanating from information asymmetry faced by investors. Furthermore, using a triple-sorting portfolio approach and proxies for financial constraint (Hadlock and Pierce, 2010; Kaplan and Zingales, 1997; Lamont, Polk, and Saá-Requejo, 2001), innovation ability (Cohen, Diether, and Malloy, 2013), and product market competition (Hou and Robinson, 2006), I show that the important role of stock illiquidity in the R&D-return relation cannot be explained by these factors. Taken together, my results suggest that illiquidity has a strong impact on R&D-intensive firms' risk-return profile and independently drives a significant portion of the positive R&D-return relation.

The remainder of this chapter is organized as follows. Section 2.2 presents the model and develops the testable hypothesis. Section 2.3 describes in detail the data used to test the hypothesis and provides summary statistics. Section 2.4 presents the empirical results. A series of subsample analyses isolating the mechanism driving my main finding are provided in Section 2.5. Finally, Section 2.6 concludes this chapter. A separate Appendix contains robustness checks and additional empirical results.

## 2.2 The Model

In this section, I derive a partial equilibrium model characterizing how the level of stock illiquidity influences the positive relation between a firm's R&D investment and expected returns. The setup of my model follows closely the classic models of innovation and R&D venture in the literature (see, among others, Berk, Green, and Naik, 1999, 2004; Gross-

man and Shapiro, 1987), where the process requires successful completion of a number of sequential steps. In particular, such steps often include tasks like setting up a laboratory or research facility, hiring appropriately skilled personnel, and conducting experiments and clinical/controlled trials. Once these vital steps are successfully completed over a passage of time, the R&D venture generates a stochastic payoff. In my model, the firm, lacking sufficient internal resources, resorts to the stock market to raise funds necessary to initiate a single multistage R&D project. It then: (1) allocates such funds to finance expenses required for successfully completing the project in time; and (2) decides on a terminal period for the project, which determines the length of the project. All these activities take place in an environment where the financial market exhibits illiquidity of the firm's stock, stemming from adverse selection. Below I outline the basic ingredients of my theoretical model and develop the intuition underlying its main prediction.[3]

#### 2.2.1.1 Technology of R&D

Let $D$ be the total "distance" to be traversed by the firm for successfully completing an R&D project and $S_t$ be the distance that has been traversed by date $t$ from an initial position, $S_0$. The incremental steps completed in any period depends on the distance already traversed in the preceding time period and the expenditure to be incurred in the current period. Formally speaking, $S_t = S_{t-1} + h(m_t)$, where the initial position $S_0 = 0$, $m_t$ is the R&D expenditure made at period $t$, and $h(m_t)$ is a function determining the progress made in period $t$. The function $h(m_t)$ is increasing and concave, signifying the diminishing returns to effort and expenditure once some progress has been made up to the preceding period. That is, $h(0) = 0$, $h'(m_t) > 0$, and $h''(m_t) < 0$. Since the firm operates in continuous time, I can write $S(t + \Delta t) - S(t) = h(m_t)\Delta t$ or $[S(t + \Delta t) - S(t)]/\Delta t \cong h(m_t)$. With $\lim \Delta t \to 0$,

$$\frac{dS}{dt} = h(m_t) \quad \text{or} \quad S_t = \int_0^t h(m_t)dt. \tag{2.1}$$

Thus, if the firm has to traverse distance $D$ in time period $T$, then the following condition must be satisfied:

$$\int_0^T h(m_t)dt \geqslant D. \tag{2.2}$$

The total expense that a firm incurs is given by

$$\int_0^T m_t e^{-rt}dt,$$

[3] Although my model describes a single R&D venture, the implications apply to firms with multiple projects.

where $r$ is the constant risk-free rate at which the firm discounts the future. The firm must raise this amount of funds either as internal equity or as external claims to finance the project.

#### 2.2.1.2 Uncertainty

The R&D project generates a constant but stochastic payoff, denoted $X$, which accrues to the firm only after successful completion of the project. The project is risky since completion of the total number of steps needed for the fruition of the project is uncertain due to risks inherent in the process of innovation. The degree of uncertainty partly depends on: (1) exogenous factors, described by a probability distribution of the project failure, which depends on time – specifically, as more time elapses, the cumulative probability of failure decreases; and (2) the "experiences" accumulated up to a given time point, measured by the number of steps completed by that time. The greater is the advancement towards the terminal date, the more steps are covered, which shifts the distribution of project failure by the first-order stochastic dominance. The implicit assumption is that as the firm completes each step, it earns incremental experience or knowledge, which lowers the probability of failure in future, provided that the R&D project does not collapse in the current period.

Formally speaking, I let $F(t)$ be the cumulative probability distribution of the firm successfully completing the R&D project on or before time $t$ and $F'(t) = f(t)$ be the corresponding density function. I also assume that there exists a time, $T_1$, which is long enough to make $F(T_1) = 1$. The following expression is an example of the cumulative probability distribution function just mentioned, where $\int_0^T h(m_t)dt$ represents experience or knowledge:

$$F(T) = \frac{T + \int_0^T h(m_t)dt}{T_1 + \int_0^{T_1} h(m_t)dt}.$$

A simple way of introducing "experience" to affect the duration of the R&D project is to make the terminal time dependent on a particular date as well as the total length of the path in the following additive form:

$$\overline{T} = T_1 + S_{T_1} \text{ with } S_{T_1} = \int_0^{T_1} h(m_t)dt.$$

#### 2.2.1.3 Information and illiquidity

I assume that the firm has insufficient internal funds but it can raise sufficient external funds to complete the R&D project as long as it earns a nonnegative payoff. In addition to uncertainty of the project, investors also face liquidity risk, in that they might need to sell

their stakes on the secondary market to other investors or dealers. Hence, before completion of the project[4], an investor may sell her financial assets (i.e., stocks) but in doing so may face an adverse selection problem. To illustrate this problem, I assume that there are two types of firm: (1) a *good* type, which could earn a payoff $X$ probabilistically if it successfully completes all the steps in the R&D project; and (2) a *bad* type, which fails with probability 1 and receives a zero payoff. I further assume that the proportions of *good* and *bad* firms are given by $\alpha$ and $1-\alpha$, respectively. At date 0, when the firm issues outside financial claims (i.e., public shares), neither investors nor entrepreneurs have any additional knowledge about the prospect of success or failure other than the proportions of *good* and *bad* types and the probability distribution of the R&D project's success and failure. However, with the passage of time and before the completion of the project's penultimate step, some insiders could obtain a signal which conveys probabilistically news about *good* and *bad* types of firm. If the true state of the world is $\omega \in \{good, bad\}$, then signal $\varphi \in \{high, low\}$ consists of a probabilistic perception of the states described as follows:

$$Pr.(\varphi = high|\omega = good) = Pr.(\varphi = low|\omega = bad) = \sigma,$$
$$Pr.(\varphi = high|\omega = bad) = Pr.(\varphi = low|\omega = good) = 1 - \sigma.$$

Thus, $\sigma \in (\frac{1}{2}, 1)$ measures the precision of the signal. The informed insiders sell whenever they receive a *bad* signal and buy whenever they receive a *good* signal. The other type of investors are liquidity traders who sell or buy due to their liquidity need.

The stock market setup follows closely to Glosten and Milgrom (1985) in the sense that buyers and sellers transact with a market maker who, upon observation of a buy or sell order, revises her expectations about the future payoff. For example, if she receives a sell order then it could be either a liquidity trader selling out of a need for cash or it could be the informed investor selling on bad news. Let the proportions of liquidity and informed traders, respectively, be $\theta$ and $1-\theta$, and $\gamma$ be the probability that the liquidity trader faces a cash crunch and so sells her stakes on the stock market. Then, conditional on a sell order, the probability that the firm will successfully complete the R&D project is

$$Pr.shock(firm\ is\ good|sell\ order) \equiv \beta = \frac{\alpha\theta\gamma + (1-\theta)\alpha(1-\sigma)}{\alpha\theta\gamma + (1-\theta)[\alpha(1-\sigma) + (1-\alpha)\sigma]}.$$

The above is also the joint probability that the investor will be able to get $R$ in the event of a liquidity shock.

[4] Investors and the firm receive a payoff only upon successful completion of the R&D project.

If the firm decides to spend $m_t$ in each period, then the discounted value of the total amount of external funds required is $\int_0^T m_t e^{-rt} dt$. Now, if the investors are promised $R$ in the event of success, then the no-arbitrage condition states that

$$F(T)e^{-rT}R\alpha[(1-\gamma)+\gamma\beta] = \int_0^T m_t e^{-rt} dt \tag{2.3}$$

or

$$e^{-rT}R = \frac{\int_0^T m_t e^{-rt} dt}{F(T)\alpha\mu}, \tag{2.3$'$}$$

where $\mu = (1-\gamma)+\gamma\beta$. In equation (2.3), $F(T)$ captures the cumulative probability of success and $e^{-rT}R\alpha$ is the discounted value of expected gross return on the R&D project. One may note that a liquidity premium ($\mu < 1$) occurs because $0 < \beta < 1$. Suppose that there are no informed traders, then

$$\theta = 1,\ \beta = \frac{\alpha\theta\gamma + (1-\theta)\alpha(1-\sigma)}{\alpha\theta\gamma + (1-\theta)[\alpha(1-\sigma)+(1-\alpha)\sigma]} = 1,\ \text{and}\ \mu = 1,$$

In this case, equation (2.3$'$) reduces to

$$e^{-rT}R = \frac{\int_0^T m_t e^{-rt} dt}{F(T)\alpha}.$$

Thus, $\mu$ is the measure of liquidity (or, equivalently, $1/\mu$ measures the level of illiquidity).[5] That is, the more illiquid the firm's stock is, the less is the value of $\beta$ or $\mu$.

### 2.2.2 Optimization

The firm's objective is to maximize the expected discounted value of its profit, subject to the constraints that: (1) the total amount spent on the R&D project is such that all required steps are successfully completed; and (2) investors must be given their expected returns equal to the amount if they would had invested at the constant risk-free rate, $r$. These constraints are given by equations (2.2) and (2.3), respectively. Thus, the firm's optimization problem can be written as

$$\begin{aligned} &\max_{\{m_t\},T} \alpha F(T)e^{-rT}(X-R) \\ \text{s.t.}\quad &\int_0^T h(m_t)dt \geqslant D \text{ and} \\ &F(T)e^{-rT}R\alpha[(1-\gamma)+\gamma\beta] = \int_0^T m_t e^{-rt} dt. \end{aligned} \tag{2.4}$$

[5] Note that the risk-free return obtains when $\alpha = F(T) = \theta = 1$. That is, there is no risk or uncertainty from either the final outcome or any liquidity risk.

To conserve space, the solution to the above optimal control program is given in Appendix A. Below I simply state the testable hypothesis derived from the solution to equation (2.4).

**Hypothesis:** The positive R&D-return relation strengthens with firm's stock illiquidity.

## 2.3 Data, R&D intensity and illiquidity measures, and summary statistics

This section describes the data used in the empirical analyses and the construction of the R&D intensity and illiquidity measures, and presents the summary statistics of variables of interest.

### 2.3.1 Data and measures of R&D intensity and illiquidity

I obtain daily and monthly stock return data from the Center for Research in Security Prices (CRSP) and a host of firm-specific accounting information from the Compustat Annual Industrial Files. My preliminary sample includes all NYSE-, AMEX-, and NASDAQ-listed ordinary common stocks (CRSP share code of 10 or 11). From this preliminary sample I exclude financial firms, which have four-digit standard industrial classification codes between 6000 and 6999, and firms with a nonpositive book value of equity. My sample period starts in January 1975 and ends in December 2016, since the accounting treatment of R&D expenses reporting was standardized in 1975 (Financial Accounting Standards Board Statement No. 2). Table 2.A1 in the Appendix reports summary statistics for this preliminary sample.

To perform all of the empirical analyses, I construct two samples, namely, the full sample and the all-but-microcaps sample, from the intersection of the Compustat database and the preliminary sample considered in Table 2.A1. Specifically, my full sample consists of all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year and a valid illiquidity estimate in a given month are obtainable. In the all-but-microcaps sample, I exclude stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution and retain the remaining NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks with both nonmissing R&D intensity and valid illiquidity estimates. Microcap firms tend to experience a higher level of stock illiquidity and to have a higher R&D intensity. Using the all-but-microcaps sample (which excludes microcaps) therefore helps mitigate the possible undue influence of microcaps on the empirical results obtained in the full sample. In line with Fama and French (1992), I further employ all accounting variables at the end of June of calendar year $t$ by using accounting information available for

the fiscal year ending in the calendar year $t-1$ from Compustat. This adjustment ensures that the accounting information is already incorporated into firms' stock prices.

Consistent with the literature (see, among others, Chan, Lakonishok, and Sougiannis, 2001; Eberhart, Maxwell, and Siddique, 2004; Gu, 2016; Li, 2011), I use two alternative measures of a firm's R&D intensity. The first is R&D expenditure scaled by market value of equity, denoted $RDME$, while the second is R&D expenditure scaled by total assets, denoted $RDAT$.[6] More specifically, $RDME$ is computed at the end of June of year $t$ as the ratio of the R&D expenditure (Compustat item XRD) at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of June of year $t$. On the other hand, $RDAT$ is computed in June of year $t$ as the ratio of R&D expenditure to total assets (Compustat item AT) at the end of the fiscal year ending in the calendar year $t-1$.

The stock illiquidity measure that I primarily adopt in this chapter is the average bid-ask spread (denoted $BAS$), computed using one month's worth of daily data with a minimum of 15 valid daily observations.[7] As an alternative to $BAS$, I further adopt the Amihud (2002) illiquidity measure, denoted $ILLIQ$.[8,9] Both the bid-ask spread and the Amihud (2002) illiquidity measure are extensively used in the empirical asset pricing literature to compute stock illiquidity (see, among others, Amihud and Mendelson, 1989; Amihud, Hameed, Kang,

[6] Both Chan, Lakonishok, and Sougiannis (2001) and Li (2011) find that their results are stronger when $RDME$ is used to capture a firm's R&D intensity.

[7] $BAS$ is calculated at the end of each month $\tau$ as

$$BAS_{i,\tau} = \frac{1}{N}\sum_{n=1}^{N}\frac{Ask_{i,n} - Bid_{i,n}}{Mid_{i,n}},$$

where $Ask_{i,n}$ and $Bid_{i,n}$ are, respectively, the ask and bid prices of stock $i$ on day $n$ from the CRSP daily data, $Mid_{i,n}$ is the average of $Ask_{i,n}$ and $Bid_{i,n}$, and $N$ is the number of days in the estimation period. A higher value of $BAS$ implies a higher level of illiquidity (or, equivalently, a lower level of liquidity). For robustness checks of my empirical findings, I also estimate two more versions of $BAS$. The first is computed at the end of each month $\tau$ using one year's worth of daily data. In a slightly different manner, the second is calculated at the end of June of each year $t$ using one year's worth of daily data. I require a minimum of 200 valid daily observations in both versions. The value of $BAS$ is updated on a monthly basis in the former, while on a yearly basis in the latter version. The results based on these alternative versions of $BAS$ are qualitatively similar to those reported in this chapter and are provided in the Appendix.

[8] Amihud (2002) illiquidity measure is defined as

$$ILLIQ_i = \frac{1}{N}\sum_{n=1}^{N}\frac{|r_{i,n}|}{DVOL_{i,n}},$$

where $r_{i,n}$ is the return of stock $i$ on day $n$, $DVOL_{i,n}$ is the dollar trading volume of stock $i$ on day $n$, and $N$ is the number of days in the estimation period. A higher value of $ILLIQ$ indicates a higher level of stock illiquidity. I follow Gao and Ritter (2010) to adjust trading volume of NASDAQ-listed stocks and compute $ILLIQ$ at the end of each month $\tau$ using one month's worth of daily data with at least 15 positive-volume days.

[9] Following Goyenko, Holden, and Trzcinka (2009), I also compute an extended Amihud (2002) measure of illiquidity, defined as the ratio of $BAS$ to average daily dollar volume. This illiquidity measure considers both cost dimension and price impact.The results reported in this chapter remain qualitatively similar when I use this proxy in the empirical analyses; these additional results are available upon request.

and Zhang, 2015; Beber and Pagano, 2013; Hameed, Kang, and Viswanathanan, 2010; Han and Lesmond, 2011; Kelly and Ljungqvist, 2012, and references therein).

To control for firm attributes that may be related to future stock returns, I construct a number of additional variables. These include past returns, book-to-market equity, and firm size. In accordance with Fama and French (1992, 1993) and Novy-Marx (2013), I calculate the book value of equity as the shareholders equity (Compustat item SEQ), plus the balance sheet deferred taxes and investment tax credit (Compustat item TXDITC), minus the book value of preferred stock (Compustat item PSTKRV). If shareholders equity is missing, I set it equal to the sum of the value of common equity (Compustat item CEQ) and the carrying value of preferred stock (Compustat item PSTK) if available, or else total assets (Compustat item AT) minus total liabilities (Compustat item LT). If the item balance sheet deferred taxes and investment tax credit is missing, I set it equal to the balance sheet deferred taxes (Compustat item TXDB) and/or the balance sheet investment tax credit (Compustat item ITCB). If the book value of preferred stock is missing, I set it equal to the liquidating value (Compustat item PSTKL) if available or else the carrying value (Compustat item PSTK). I resort to the Davis, Fama, and French (2000) book values of equity from the Internet Data Library maintained by Kenneth R. French to fill in missing values of the book value of equity.[10] Following Fama and French (1992, 1993), I then compute the book-to-market ($BM$) ratio at the end of June of year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. Meanwhile, the market value of equity ($ME$) is computed as absolute price times number of equity shares outstanding at the end of June of each year $t$.

I also compute the average abnormal returns on portfolios (described in Sections 4.3 and 5) relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. For this purpose, time-series data on the pricing factors (i.e., market, size, value, momentum, profitability, and investment) of these models and monthly risk-free security returns are again retrieved from the Internet Data Library maintained by Kenneth R. French.

[10] For details, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

### 2.3.2 Summary statistics

My empirical analyses begin by presenting summary statistics for the full sample, comprising stocks with both nonmissing $RDME$ and valid $BAS$ estimates.[11] Panel A of Table 2.1 reports the time-series averages of the cross-sectional summary statistics for my chosen R&D intensity and illiquidity measures. As can be seen, in the average month, the mean value of $BAS$ is 0.06 and the median value of $BAS$ is 0.04. The average cross-sectional standard deviation of $BAS$ is 0.06. In the average month, the maximum value of 0.67 for $BAS$ is more than 11 standard deviations above the mean. Analyzing the R&D intensity measure $RDME$, I find that, in the average year, the mean and median values are 0.07 and 0.03, respectively. The average cross-sectional standard deviation of $RDME$ is 0.14. The maximum value of $RDME$ in the average year of 2.88 is more than 20 standard deviations above the mean. There are 2037 stocks with valid values of both $BAS$ and $RDME$ in the average month.

To help interpret the results in subsequent sections, I report equal-weighted average values of characteristics, including $BAS$, $ME$, and $BM$, for portfolios sorted on R&D intensity (measured by $RDME$) in Panel B of Table 2.1. At the end of June of each year $t$, stocks are sorted into three portfolios using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $RDME$. I keep the stocks in the assigned portfolios for the subsequent 12 months. This procedure is repeated at the end of June of each year $t$. It is noticeable that stocks in the High $RDME$ portfolio tend to be the most illiquid, followed by stocks in the Low $RDME$ portfolio. This observation, therefore, suggests a nonlinear relation between R&D intensity and stock illiquidity. The $BM$ ratios of $RDME$-sorted portfolios also display a nonlinear relation with R&D intensity, and the pattern is similar to that for illiquidity. In contrast, stocks in the High $RDME$ portfolio tend to be the smallest, with an average market capitalization of \$662.93 million. This finding is also in line with Li (2011), who shows that firms with a higher R&D intensity tend to be smaller.

Panel C of Table 2.1 reports the value-weighted and equal-weighted average monthly excess returns for the portfolios sorted on stock illiquidity and R&D intensity. The idea behind this empirical exercise is to investigate whether conventional univariate sorts on illiquidity or R&D intensity alone yield a pattern in average excess returns. In the case of

[11] Table 2.A2 in the Appendix provides summary statistics for the all-but-microcaps sample. For brevity, summary statistics of the samples with $\{RDME, ILLIQ\}$ and $\{RDAT, BAS\}$ combinations are omitted in this chapter; these are available upon request.

$BAS$ ($RDME$) as the sort variable, I group stocks into three portfolios using the breakpoints set to the bottom 30%, middle 40%, and top 30% of the ranked values of $BAS$ ($RDME$) at the end of month $\tau$ (June of each year $t$). Analyzing the portfolios formed by sorting on $BAS$, I find that the value-weighted average excess portfolio returns exhibit neither a monotonically increasing nor a monotonically decreasing pattern. In addition, the value-weighted average return of $-0.28\%$ per month on the high-minus-low illiquidity portfolio is statistically insignificant at conventional levels ($t$-statistic $= -0.70$). When looking at the equal-weighted average monthly excess portfolio returns, I see that a simple sort on $BAS$ yields a monotonically increasing pattern in returns. However, the monthly average return of 0.25% for the high-minus-low portfolio is statistically indistinguishable from zero ($t$-statistic $= 0.81$). Examining the portfolios formed by sorting on $RDME$, I observe that the value-weighted average monthly excess portfolio returns increase monotonically, from 0.55% for the Low $RDME$ portfolio to 1.03% for the High $RDME$ portfolio. A similar monotonically increasing pattern in excess return arises for the equal-weighted portfolios. The value-weighted (equal-weighted) average return of 0.48% (0.94%) per month for the high-minus-low $RDME$ is statistically significant, with a Newey and West (1987)-adjusted $t$-statistic of 2.61 (4.88).

In Panel D of Table 2.1, I repeat the univariate portfolio analyses of Panel C but with stocks sorted into two sets of quintile portfolios. Hence, the Low $BAS$ ($RDME$) portfolio consists of the 20% of stocks with the lowest illiquidity (R&D intensity), while the High $BAS$ ($RDME$) portfolio consists of the 20% of stocks with the highest illiquidity (R&D intensity). Once again, the value-weighted and equal-weighted average excess returns on $BAS$-sorted portfolios exhibit no meaningful pattern. The high-minus-low $BAS$ portfolio generates value-weighted and equal-weighted average returns of $-0.03\%$ ($t$-statistic $= -0.05$) and 0.50% ($t$-statistic $= 1.37$) per month, respectively. On the other hand, both the value-weighted and equal-weighted average excess returns on R&D intensity sorted portfolios increase nearly monotonically with $RDME$ (the exception is portfolio 2). Furthermore, the high-minus-low $RDME$ portfolio generates an equal-weighted average return of 1.04% per month, which is both economically large and statistically significant ($t$-statistic $= 4.47$). Although the value-weighted average monthly return of 0.31% for the high-minus-low $RDME$ portfolio is statistically indistinguishable from zero at conventional levels ($t$-statistic $= 1.41$), the portfolio generates an average return of 2.22% per month ($t$-statistic $= 3.99$) among illiquid stocks (see Table 2.A22 in the Appendix).

## 2.4 Empirical results

This section tests my model, which predicts that the positive R&D-return relation is stronger among illiquid stocks.[12] I follow two complementary empirical methodologies to examine the model's prediction: a cross-sectional regression approach and a double-sorted portfolio approach. These allow us to assess the robustness of my results.

### 2.4.1 Cross-sectional regressions

I employ the Fama and MacBeth (1973) cross-sectional regressions to examine the power of R&D intensity to predict future returns among stocks with low and high illiquidity. This analysis allows us to simultaneously control for other firm-specific characteristics that can predict returns (see, for example, Fama and French, 2008). At the end of each month $\tau$, stocks are sorted into three illiquidity groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $BAS$ in month $\tau$. Then, in each month from July of year $t$ to June of year $t+1$, I run cross-sectional regressions in the following form for the Low (or, equivalently, liquid) and High (or, equivalently, illiquid) groups separately:

$$R_{i,\tau+1} = \delta_{0,\tau} + \delta_{1,\tau} R_{1,1_{i,\tau}} + \delta_{2,\tau} R_{12,2_{i,\tau}} + \delta_{3,\tau} \ln(BM)_{i,\tau} + \delta_{4,\tau} \ln(ME)_{i,\tau} + \delta_{5,\tau} RDME_{i,\tau} + \epsilon_{i,\tau+1}, \tag{2.5}$$

where $R_i$ is the monthly return on stock $i$, $R_{1,1}$ is the prior one-month return, $R_{12,2}$ is the prior one-year return skipping the last month (i.e., return from month $\tau-12$ to month $\tau-2$), $\ln(ME)$ is the natural logarithm of market value of equity at the end of June of year $t$, $\ln(BM)$ is the natural logarithm of book-to-market ratio calculated at the end of June of year $t$, and $RDME$ is the proxy for R&D intensity, which is computed at the end of June of year $t$. To reduce the undue influence of outliers on the results, I winsorize all independent variables at the 1% and 99% levels on a monthly basis prior to running the cross-sectional regressions. Moreover, following Fama and French (2008), I compute the time-series averages of the differences in slope and intercept coefficient estimates between the High and Low illiquidity groups. This enables us to empirically examine whether or not the positive R&D-return relation strengthens with the level of stock illiquidity.

Table 2.2 reports the time-series average slope and intercept coefficient estimates from

[12] I report empirical results based on the $\{RDME, BAS\}$ combination of R&D intensity and illiquidity measures throughout this chapter. The results obtained by using alternative R&D intensity and illiquidity measure combinations, such as $\{RDME, ILLIQ\}$ and $\{RDAT, BAS\}$, are qualitatively similar to those presented in this chapter. To conserve space, these additional results are reported in the Appendix Tables 2.A15–2.A20.

the monthly Fama and MacBeth (1973) cross-sectional regressions. After controlling for the well-known effects of size, book-to-market, short-term reversal ($R_{1,1}$), and momentum ($R_{12,2}$), the average coefficient estimate on R&D intensity appears to be much larger for illiquid stocks (High group) than for liquid stocks (Low group), both in magnitude and in statistical significance. Specifically, in Panel A, which utilizes the full sample (described in Section 2.3.1) to construct the three illiquidity groups, I see that the estimated average coefficient on $RDME$ for stocks in the High illiquidity group is 5.69 with a Newey and West (1987)-adjusted $t$-statistic of 6.67. In contrast, the estimated average coefficient of 0.95 on $RDME$ for stocks in the Low illiquidity group is statistically indistinguishable from zero ($t$-statistic = 1.31). More importantly, the average spread between the estimated slope coefficients on $RDME$ for stocks in the High and Low illiquidity groups is 4.74, with a corresponding $t$-statistic of 6.00. I observe qualitatively similar results in Panel B, which utilizes the all-but-microcaps sample (described in Section 2.3.1) to create the illiquidity groups. The average coefficient estimate on $RDME$ is 6.23 ($t$-statistic = 3.29) for stocks in the High illiquidity group, while it is only 0.28 ($t$-statistic = 0.24) for stocks in the Low illiquidity group. Notably, the estimated average slope spread on $RDME$ between the High and Low groups is 5.95; this slope estimate is statistically significant ($t$-statistic = 3.48). These results also suggest that the presence of microcaps in the full sample are unlikely to drive the positive and significant R&D-return relation observed among illiquid stocks in Panel A.[13]

My empirical results remain robust to an extended sample period that starts in January 1963 and ends in December 2016.[14] The estimated average slope spreads on $RDME$ between the High and Low illiquidity groups are 3.76 ($t$-statistic = 4.69) and 5.01 ($t$-statistic = 3.16) for the full sample and the all-but-microcaps sample, respectively. I show these results in the Appendix Table 2.A4. When the monthly stock returns during the period from January 1975 through December 2016 are adjusted following Shumway (1997) for delistings, the results are very similar to those reported in Table 2.2. For example, Table 2.A5 in the Appendix shows that the estimated average slope spreads on $RDME$ between the High and Low illiquidity groups are 4.52 ($t$-statistic = 5.76) and 5.99 ($t$-statistic = 3.55), respectively, for the full sample and the all-but-microcaps sample.

[13] Similar empirical results are obtained when I include industry dummies as additional controls in the Fama and MacBeth (1973) cross-sectional regressions; these are reported in the Appendix Table 2.A3.

[14] I follow Gu (2016), who examines the positive R&D-return relation in competitive and noncompetitive industries by using R&D expenditure data from 1963 to 2013. But most empirical studies (see, for example, Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013; Li, 2011) use data from or after 1975 due to accounting standardization of R&D expenses reporting.

I also conduct the Fama and MacBeth (1973) cross-sectional regression analyses for subperiods. My motivation for this empirical investigation is the reduction in the NYSE and AMEX minimum tick size from \$1/16th to \$1/100th in January 2001. The NASDAQ completed its implementation of decimalization shortly after, in April 2001. It is possible that the results in Table 2.2 are mainly driven by observations from the predecimalization period, which is largely characterized by a higher level of stock illiquidity (see, for example, Chordia, Roll, and Subrahmanyam, 2008, 2011). I therefore skip observations from 2001 to avoid confounding effects and split the sample period into two subperiods: 1975–2000 and 2002–2016. Tables 2.A6 and IA7 in the Appendix provide evidence that a significantly positive R&D-return relation among illiquid stocks holds for both subperiods.

Furthermore, I investigate whether my empirical findings differ across high-tech and low-tech industries. The idea behind this examination follows from Chan, Martin, and Kensinger (1990), who show that high-tech firms experience higher abnormal returns on average than low-tech firms following an announcement of an increase in R&D spending. To rule out the possible impact of industry types on my empirical results, I proceed by partitioning both the full sample and the all-but-microcaps sample into high-tech firms and low-tech firms, based on the Fama and French 12-industry group classification system.[15] Analogous to Table 2.2, I then conduct the monthly Fama and MacBeth (1973) cross-sectional regression analyses. Table 2.A8 in the Appendix shows evidence of a significantly positive R&D-return relation among illiquid stocks in both high-tech and low-tech industries. This suggests that the findings in Table 2.2 are unlikely to be driven by firms in a particular industry. In summary, my results from a series of cross-sectional regression analyses indicate that the positive R&D-return relation is much stronger among illiquid stocks.

### 2.4.2 Cross-sectional regressions with illiquidity dummies

I continue examining the effect of stock illiquidity on the positive R&D-return relation by estimating the Fama and MacBeth (1973) cross-sectional regressions augmented with illiquidity dummy and interaction variables. I use several different cross-sectional specifications for this purpose. To be consistent with the cross-sectional analyses in Section 2.4.1, two illiquidity dummy variables are created by sorting stocks into three groups based on the breakpoints set to the 30th and 70th percentiles of the ranked values of $BAS$ in month $\tau$. Then, in each month from July of year $t$ to June of year $t+1$, I estimate the following

[15] For details on these industry classifications, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

cross-sectional regressions:

$$R_{i,\tau+1} = \delta_{0,\tau} + \delta'_{\tau} C_{i,\tau} + \epsilon_{i,\tau+1}, \tag{2.6}$$

$$R_{i,\tau+1} = \delta_{0,\tau} + \delta'_{\tau} C_{i,\tau} + \delta_{6,\tau} RDME_{i,\tau} * BAS_{L_{i,\tau}} + \delta_{7,\tau} BAS_{L_{i,\tau}} + \epsilon_{i,\tau+1}, \tag{2.7}$$

$$R_{i,\tau+1} = \delta_{0,\tau} + \delta'_{\tau} C_{i,\tau} + \delta_{6,\tau} RDME_{i,\tau} * BAS_{H_{i,\tau}} + \delta_{7,\tau} BAS_{H_{i,\tau}} + \epsilon_{i,\tau+1}, \tag{2.8}$$

$$\begin{aligned} R_{i,\tau+1} = {} & \delta_{0,\tau} + \delta'_{\tau} C_{i,\tau} + \delta_{6,\tau} RDME_{i,\tau} * BAS_{H_{i,\tau}} + \delta_{7,\tau} RDME_{i,\tau} * BAS_{L_{i,\tau}} \\ & + \delta_{8,\tau} BAS_{H_{i,\tau}} + \delta_{9,\tau} BAS_{L_{i,\tau}} + \epsilon_{i,\tau+1}, \end{aligned} \tag{2.9}$$

where $C_{i,\tau}$ is a vector of same continuous independent variables considered in equation (2.5), and $BAS_H$ ($BAS_L$) is a dummy variable that is equal to one for stocks in the High (Low) illiquidity group in a given month and is zero otherwise. I also winsorize all continuous independent variables at the 1% and 99% levels on a month-by-month basis prior to running the cross-sectional regressions.

Consistent with my results in Table 2.2, the time-series averages of the monthly cross-sectional regression estimates in Table 2.3 confirm that the positive R&D-return relation strengthens with the level of stock illiquidity. As can be seen from the baseline monthly cross-sectional regressions (equation (2.6)) in Panel A, using the full sample, R&D intensity measured by $RDME$ has a significantly positive relation with future stock returns. The average coefficient estimate on $RDME$ is 4.26, with a corresponding $t$-statistic of 5.35. When considering the monthly cross-sectional regressions specified by equation (2.7), I observe that the average coefficient estimate on the interaction variable $RDME * BAS_L$ is $-5.03$ ($t$-statistic $= -7.10$). The sum of the average coefficient estimates on $RDME$ and $RDME * BAS_L$ is $-0.08$ ($t$-statistic $= -0.11$). This result suggests that R&D intensity has no significantly positive effect on future returns for stocks in the Low illiquidity group.

Turning now to the cross-sectional regressions specified by equation (2.8), I find that the estimated average coefficient on the variable of interest, $RDME * BAS_H$, is 4.07, which is both economically and statistically significant ($t$-statistic $= 5.73$). To get an idea of the magnitude of this result, I multiply the average coefficient estimate by the standard deviation of $RDME$ in the average month.[16] All else being equal, a one-standard deviation increase in $RDME$ is associated with a 39 basis point higher future return per month for stocks in the High illiquidity group relative to stocks in all other groups. The sum of the average coefficients on $RDME$ and $RDME * BAS_H$, which is the slope estimate of $RDME$ for

[16] The monthly average cross-sectional standard deviation of $RDME$ is 0.095 (0.042) for the full sample (all-but-microcaps sample) containing firms with nonmissing values of $R_{1,1}$, $R_{12,2}$, $BM$, $ME$, and $RDME$.

stocks in the High illiquidity group, turns out to be 6.37 and statistically significant ($t$-statistic = 7.64). I find, for the cross-sectional regressions in equation (2.9), that the average coefficient estimates on the interaction variables $RDME * BAS_L$ and $RDME * BAS_H$ are, respectively, $-3.49$ ($t$-statistic = $-5.37$) and 3.12 ($t$-statistic = 4.32). All of these results based on the full sample demonstrate that the positive R&D-return relation observed in the baseline cross-sectional regression analyses is an average effect of firms with different levels of stock illiquidity. In fact, the positive R&D-return relation is much stronger among illiquid stocks.

Panel B of Table 2.3 reports the results based on the all-but-microcaps sample, which are qualitatively similar to those obtained using the full sample. The average coefficient estimate of 3.36 on $RDME$ from the baseline cross-sectional regressions (equation (2.6)) is statistically significant ($t$-statistic = 2.20). Looking at the estimates from the cross-sectional regressions specified by equation (2.7), I find that the average coefficient on the interaction variable $RDME * BAS_L$ is $-4.98$ ($t$-statistic = $-3.57$). Moreover, the sum of coefficient estimates on $RDME$ and $RDME * BAS_L$ is $-0.60$, which is economically small and statistically indistinguishable from zero ($t$-statistic = $-0.53$). The results, therefore, imply the absence of a significantly positive R&D-return relation among liquid stocks, or, equivalently, stocks in the Low illiquidity group.

Considering the monthly cross-sectional regressions in equation (2.8), I notice that the average coefficient estimate of 5.08 on the interaction variable $RDME * BAS_H$ is statistically significant at conventional levels ($t$-statistic = 3.58). This in turn implies that, all else being equal, a one-standard deviation increase in $RDME$ is associated with a 21 basis point higher future return per month for stocks in the High illiquidity group relative to those in the Medium and Low illiquidity groups. The sum of the average coefficient estimates on $RDME$ and $RDME * BAS_H$ is 6.86, with a corresponding $t$-statistic of 3.75. I also notice that the average coefficient estimates on the interaction variables $RDME * BAS_L$ and $RDME * BAS_H$ are, respectively, $-3.28$ ($t$-statistic = $-2.41$) and 3.98 ($t$-statistic = 2.64) in the monthly cross-sectional regressions specified by equation (2.9). Taken together, consistent with my hypothesis, the results in Panels A and B show that, after controlling for firm-specific characteristics, such as size, book-to-market equity, short-term reversal, and momentum, the power of R&D intensity to predict future returns is stronger in the cross-section of illiquid stocks. In other words, the level of stock illiquidity explains a significant portion of the positive R&D-return relation that I observe in the baseline cross-sectional regression analyses.

### 2.4.3 Double-sorted portfolios

To further examine the robustness of my preceding empirical results, I conduct a bivariate independent-sort portfolio analysis using information about both a firm's R&D intensity and its level of stock illiquidity. At the end of each month $\tau$, I sort stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of illiquidity measured by $BAS$ in month $\tau$. Independently, at the end of June of each year $t$, I also sort stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $RDME$ computed at the end of June of year $t$. The stocks are held in the assigned R&D groups for the subsequent 12 months. The monthly intersections of the illiquidity and R&D intensity groups result in nine portfolios.[17] I compute the value-weighted average excess returns for portfolios constructed using the full sample, while the equal-weighted average excess returns for portfolios are computed using the all-but-microcaps sample.

In Table 2.4, I report the monthly excess returns and abnormal returns (i.e., alphas in the asset pricing models) on R&D intensity portfolios in the Low illiquidity (or, equivalently, liquid) and the High illiquidity (or, equivalently, illiquid) groups. The results show that the positive R&D-return relation exists only among illiquid stocks. In Panel A, which utilizes stocks in the full sample, I find that the value-weighted average monthly return of 1.57% for the high-minus-low $RDME$ portfolio in the High illiquidity group is statistically significant ($t$-statistic = 4.79). Moreover, the value-weighted average excess returns of $RDME$ portfolios increase monotonically when moving from the Low R&D-intensity portfolio $RDME_L$ to the High R&D-intensity portfolio $RDME_H$. A monotonically increasing pattern can also be seen for the monthly average abnormal returns. The magnitudes of the FF3, FFC, and FF5 model alphas on the high-minus-low $RDME$ portfolio are large; they are 1.59% ($t$-statistic = 4.85), 1.36% ($t$-statistic = 3.50), and 1.47% ($t$-statistic = 4.65), respectively.

However, a completely different picture emerges for R&D-intensity portfolios in the Low illiquidity group. For example, the value-weighted average return is only 0.08% ($t$-statistic = 0.51) per month for the high-minus-low $RDME$ portfolio. Neither the average excess returns nor the average abnormal returns on portfolios displays a monotonically increasing pattern similar to that of the High illiquidity group. For the high-minus-low $RDME$ portfolio, the value-weighted average abnormal returns relative to the three asset pricing models are all negative and statistically insignificant. In particular, the FF3, FFC, and FF5 model alphas

[17] I also perform 4×4 and 5×5 independent-sort portfolio analyses. Appendix Tables 2.A21 and 2.A22 show that the results are much stronger than those reported in this chapter.

are, respectively, −0.18% ($t$-statistic = −1.07), −0.08% ($t$-statistic = −0.46), and −0.12% ($t$-statistic = −0.72).

The results based on the all-but-microcaps sample in Panel B are consistent with those based on the full sample in Panel A. When analyzing the High illiquidity group, I see that the equal-weighted average monthly return on the high-minus-low $RDME$ portfolio is 1.05%, which is statistically significant ($t$-statistic = 3.80). In addition, the equal-weighted average excess returns of $RDME$ portfolios increase monotonically when moving from the Low R&D-intensity portfolio $RDME_L$ to the High R&D-intensity portfolio $RDME_H$. Furthermore, I observe a monotonically increasing pattern for equal-weighted average abnormal returns on portfolios. The FF3, FFC, and FF5 model alphas on the high-minus-low $RDME$ portfolio are 1.03% ($t$-statistic = 3.73), 1.04% ($t$-statistic = 3.86), and 1.12% ($t$-statistic = 4.44), respectively. On the other hand, the equal-weighted average return is only 0.11% ($t$-statistic = 1.09) per month for the high-minus-low $RDME$ portfolio in the Low illiquidity group. Notably, the FF3, FFC, and FF5 model alphas on the high-minus-low R&D-intensity portfolio turn out to be 0.00% ($t$-statistic = 0.03), 0.04% ($t$-statistic = 0.41), and 0.09% ($t$-statistic = 0.91), respectively. In summary, the results obtained from the independent double-sorted portfolio analyses show novel evidence of an economically large and statistically significant R&D premium only among illiquid stocks. Moreover, the R&D premium among illiquid stocks persists even after adjusting for risk using all three asset pricing models. These results support my hypothesis and are clearly in line with earlier findings from the Fama and MacBeth (1973) cross-sectional regressions.

## 2.5 Tests of alternative mechanisms

In this section, I conduct trivariate-sort portfolio analyses showing that the level of stock illiquidity independently drives a significant portion of the positive R&D-return relation. To do so, my portfolio analyses separately control for firm-specific characteristics, such as financial constraints, innovation ability, and product market competitiveness, which have been shown to play a role in the positive R&D-return relation in prior studies.

### 2.5.1 Financial constraints

First, I examine the effect of financial constraints on my finding that the return predictive power of R&D intensity strengthens with the level of illiquidity. Li (2011) shows that the positive R&D-return relation exists only among financially constrained firms. In this subsection, I show empirically that financial constraints cannot explain the important role

that illiquidity plays in the relation between R&D intensity and future stock returns. To begin with, I divide both the full sample and the all-but-microcaps sample into financially constrained and financially unconstrained subsamples based on the median value of the distribution of the KZ index developed in Kaplan and Zingales (1997).[18] More precisely, the financially constrained subsample includes stocks above the median, whereas the financially unconstrained subsample includes stocks below the median. For each of these subsamples, I then continue independent double sorts, on illiquidity and R&D intensity, similar to the procedure in Section 2.4.3.

Table 2.5 shows the results for financially constrained and financially unconstrained subsamples. I report the value-weighted (equal-weighted) average excess returns and abnormal returns for portfolios based on the full sample (all-but-microcaps sample). As can be seen in Panels A and B, controlling for financial constraints does not weaken the return predictive power of R&D intensity among illiquid stocks. The significantly positive return and abnormal returns on the high-minus-low R&D-intensity portfolio prevail only in the High illiquidity group, in both the financially constrained and the financially unconstrained subsamples. For example, when analyzed using the financially constrained subsample of the full sample, the value-weighted average monthly return of 1.36% on the high-minus-low $RDME$ portfolio in the High illiquidity group is statistically significant ($t$-statistic = 3.00). After adjusting for risk using the factor pricing models, the R&D premium still persists; the alphas relative to the FF3, FFC, and FF5 models are, respectively, 1.61% ($t$-statistic = 3.90), 1.30% ($t$-statistic = 2.63), and 1.87% ($t$-statistic = 4.60). Both the value-weighted average excess returns and abnormal returns on portfolios increase monotonically with R&D intensity. However, the value-weighted average return on the high-minus-low $RDME$ portfolio in the Low illiquidity group is only 0.15% ($t$-statistic = 0.55) per month. The corresponding alphas relative to the FF3, FFC, and FF5 models are, respectively, −0.07% ($t$-statistic = −0.24), 0.01% ($t$-statistic = 0.03), and 0.19% ($t$-statistic = 0.64). The absence of a significantly positive R&D premium in the Low illiquidity group suggests that financial constraints do not seem to affect the relation between R&D intensity and future returns once the level of stock illiquidity is controlled for.

[18] The reason for using the KZ index in this subsection is due to Li (2011). The author shows that the KZ index produces a significantly larger financial constraint premium across subsamples, split by R&D intensity and size, than do other popular measures of financial constraint such as the SA index developed in Hadlock and Pierce (2010), the WW index developed in Whited and Wu (2006), or age (see Table 2.5 in Li (2011)). But for robustness check, I also use the SA index and show, in the Appendix Table 2.A23, that the results are qualitatively similar to those reported in this subsection. By construction, the value of the KZ index/SA index is higher for a more financially constrained firm. The details of the computation of the KZ index are presented in Kaplan and Zingales (1997) and Lamont, Polk, and Saá-Requejo (2001). The SA index, which is a combination of asset size and firm age, is computed following Hadlock and Pierce (2010).

An examination of the financially unconstrained subsample of the full sample shows that the value-weighted average monthly return on the high-minus-low $RDME$ portfolio in the High illiquidity group is 1.14% and statistically significant ($t$-statistic of 3.08). The average abnormal returns of this difference portfolio relative to the FF3, FFC, and FF5 models are, respectively, 1.00% ($t$-statistic = 2.67), 1.08% ($t$-statistic = 2.77), and 1.21% ($t$-statistic = 3.19) per month. In addition, a monotonically increasing pattern prevails for both the value-weighted average excess returns and abnormal returns on portfolios when moving from the Low R&D-intensity portfolio $RDME_L$ to the High R&D-intensity portfolio $RDME_H$. In sharp contrast, I see that the value-weighted average return on the high-minus-low $RDME$ portfolio in the Low illiquidity group is only 0.11% ($t$-statistic = 0.60) per month. The alpha values on this difference portfolio relative to the FF3, FFC, and FF5 models are also very small, both economically and statistically; they are, respectively, −0.08% ($t$-statistic = −0.44), 0.08% ($t$-statistic = 0.45), and 0.08% ($t$-statistic = 0.38).

When I analyze the financially constrained subsample of the all-but-microcaps sample, it can be seen that the equal-weighted average monthly return on the high-minus-low $RDME$ portfolio in the High illiquidity group is 0.70%, with a corresponding $t$-statistic of 1.97. The equal-weighted average monthly abnormal returns of this portfolio relative to the FF3, FFC, and FF5 models are 0.72% ($t$-statistic = 2.08), 0.65% ($t$-statistic = 1.70), and 0.93% ($t$-statistic = 2.68), respectively. Conversely, the equal-weighted average return on the high-minus-low $RDME$ portfolio in the Low illiquidity group is only −0.18% ($t$-statistic = −1.06) per month. The corresponding alphas relative to the FF3, FFC, and FF5 models are all negative and statistically insignificant; in fact, they are −0.28% ($t$-statistic = −1.54), −0.21% ($t$-statistic = −1.19), and −0.22% ($t$-statistic = −1.21), respectively. From the financially unconstrained subsample, I once again find that the equal-weighted average monthly return of 0.14% on the high-minus-low $RDME$ portfolio in the Low illiquidity group is statistically indistinguishable from zero ($t$-statistic = 1.47). The monthly average abnormal returns on this portfolio relative to the FF3, FFC, and FF5 models are 0.03% ($t$-statistic = 0.36), 0.09% ($t$-statistic = 1.02), and 0.12% ($t$-statistic = 1.30), respectively. But the equal-weighted average monthly return of 0.68% on the high-minus-low $RDME$ portfolio in the High illiquidity group is statistically significant ($t$-statistic = 3.09). The FF3, FFC, and FF5 model alphas on this difference portfolio are 0.62% ($t$-statistic = 2.83), 0.69% ($t$-statistic = 3.15), and 0.79% ($t$-statistic = 3.85), respectively. It is worth mentioning that the positive R&D-return relation appears to be stronger in the financially constrained subsample – an observation similar to that reported in Li (2011). Collectively, the results in Table 2.5 demonstrate that

financial constraints cannot explain the important role that stock-level illiquidity plays on the positive R&D-return relation.

### 2.5.2 Innovation ability

I next investigate the effect of a firm's innovation ability on my finding. Cohen, Diether, and Malloy (2013) show that R&D intensity predicts future stock returns only when firms have a high ability to translate R&D activities into real sales growth. Specifically, GoodR&D firms (i.e., firms with high R&D intensity and high innovation ability) earn substantially higher future stock returns than BadR&D firms (i.e., firms with high R&D intensity and low innovation ability). In this subsection, I show that my finding is unaffected after controlling for innovation ability. Consistent with Cohen, Diether, and Malloy (2013), I compute a firm's ability to innovate as the average of the slope coefficient estimates from the time-series regressions of sales growth on the past six years of R&D investments (i.e., R&D expenditure scaled by sales).[19] Both the full sample and the all-but-microcaps sample are divided separately into low innovation ability (i.e., below the median) and high innovation ability (i.e., above the median) subsamples. Analogous to the preceding section, I then repeat independent double sorts, on stock illiquidity and R&D intensity, for each of these subsamples.

The results in Table 2.6 demonstrate that innovation ability does not weaken my preceding finding that the positive relation between R&D intensity and future stock returns strengthens with the level of illiquidity. Both in the low innovation ability and the high innovation ability subsamples, the high-minus-low R&D-intensity portfolio generates a positive and statistically significant return only in the High illiquidity group. For example, when the low innovation ability subsample constructed from the full sample is examined in Panel A of Table 2.6, I see that the high-minus-low $RDME$ portfolio in the High illiquidity group generates a value-weighted average monthly return of 0.70% ($t$-statistic = 1.75). The corresponding alpha values relative to the FF3, FFC, and FF5 models are 0.66% ($t$-statistic = 1.66), 0.73% ($t$-statistic = 1.59), and 0.78% ($t$-statistic = 1.81), respectively. On the other hand, the high-minus-low $RDME$ portfolio in the Low illiquidity group generates a value-weighted average monthly return of only 0.36%, which is also statistically insignificant at conventional levels ($t$-statistic = 1.41). The value-weighted average monthly abnormal returns of this difference portfolio relative to the FF3, FFC, and FF5 models are, respectively,

[19] Cohen, Diether, and Malloy (2013) use eight years of past data for each firm-level regression. The authors show that their results are insensitive to estimation windows of 6–10 years. I use six years of past data to run these regressions. This allows us to have more observations estimated for a firm's innovation ability. The details of the estimation procedure can be found in Cohen, Diether, and Malloy (2013).

0.25% ($t$-statistic = 1.00), 0.29% ($t$-statistic = 1.18), and 0.23% ($t$-statistic = 0.95).

When the high innovation ability subsample constructed from the full sample is examined in Panel B, I observe that both the value-weighted average excess returns and abnormal returns on portfolios increase monotonically with R&D intensity in the High illiquidity group. The high-minus-low $RDME$ portfolio generates a value-weighted average return of 0.81% per month, with a corresponding $t$-statistic of 1.97. But in the Low illiquidity group, the portfolio returns and abnormal returns do not show a pattern similar to that in the High illiquidity group. In addition, the average return and abnormal returns on the high-minus-low R&D-intensity portfolio are much smaller and are all statistically insignificant. Specifically, the value-weighted average monthly return on the high-minus-low $RDME$ portfolio is 0.32% ($t$-value = 1.53). This result also indicates that a firm's innovation ability is unlikely to affect the positive relation between R&D intensity and future returns once its stock-level illiquidity is controlled for.

A pattern very similar to that of the full sample emerges when examining the low innovation ability and the high innovation ability subsamples constructed from the all-but-microcaps sample. In the case of the low innovation ability subsample, the high-minus-low $RDME$ portfolio generates an equal-weighted average monthly return of 0.51% ($t$-statistic = 1.80) in the High illiquidity group. The equal-weighted average abnormal returns on this portfolio relative to the FF3, FFC, and FF5 models are, respectively, 0.54% ($t$-statistic = 1.96), 0.57% ($t$-statistic = 2.16), and 0.75% ($t$-statistic = 2.53) per month. Moreover, the equal-weighted average excess returns and abnormal returns of $RDME$ portfolios increase monotonically when moving from the Low R&D-intensity portfolio $RDME_L$ to the High R&D-intensity portfolio $RDME_H$. Conversely, the equal-weighted average return on the high-minus-low $RDME$ portfolio in the Low illiquidity group is 0.21% ($t$-statistic = 1.31) per month. The monthly average abnormal returns of this difference portfolio relative to the FF3, FFC, and FF5 models are all statistically insignificant; specifically, they are 0.17% ($t$-statistic = 1.11), 0.17% ($t$-statistic = 1.12), and 0.21% ($t$-statistic = 1.43), respectively. In the high innovation ability subsample, I notice that the equal-weighted average monthly return of 0.09% on the high-minus-low $RDME$ portfolio in the Low illiquidity group is statistically insignificant at conventional levels ($t$-statistic = 0.58). But the equal-weighted average monthly return of 0.70% on the high-minus-low $RDME$ portfolio in the High illiquidity group is statistically significant ($t$-statistic = 3.00). The corresponding monthly average abnormal returns relative to the FF3, FFC, and FF5 models are 0.58% ($t$-statistic = 2.65), 0.59% ($t$-statistic = 2.72), and 0.44% ($t$-statistic = 1.89), respectively. To sum up, the re-

sults in Table 2.6 indicate that the positive R&D-return relation among illiquid stocks is stronger in the high innovation ability subsample, which is consistent with Cohen, Diether, and Malloy (2013). More importantly, illiquidity independently drives a significant portion of the positive relation between R&D intensity and future stock returns.

### 2.5.3 Product market competition

Finally, I explore the effect of product market competition on my finding. Gu (2016) has recently shown that the positive relation between R&D intensity and future stock returns exists only for firms in competitive industries. In this subsection, I show empirically that the strengthening of the return predictive power of R&D intensity with the level of stock illiquidity remains unaffected after controlling for product market competition. As in Gu (2016), I follow Hou and Robinson (2006) to measure product market competition using the Herfindahl-Hirschman Index.[20] I divide both the full sample and the all-but-microcaps sample separately into low competition and high competition subsamples based on the median value of the distribution of HHI. Using each of these two subsamples, I then continue independent double sorts on stock illiquidity and firm's R&D intensity.

Table 2.7 reports the results for the low competition (i.e., above the median) and the high competition (i.e., below the median) subsamples. I see that after controlling for product market competition, my main finding holds regardless of the sample composition. In Panel A, where the low competition subsample of the full sample is examined, the value-weighted average monthly return on the high-minus-low $RDME$ portfolio in the High illiquidity group turns out to be 1.69% and statistically significant ($t$-statistic = 3.90). The R&D premium persists after adjusting for risk using the asset pricing models. Specifically, this portfolio generates monthly average abnormal returns of 1.68% ($t$-statistic = 4.02) relative to the FF3 model, 1.48% ($t$-statistic = 2.89) relative to the FFC model, and 1.74% ($t$-statistic = 4.16) relative to the FF5 model. Moreover, the value-weighted average excess returns and abnormal returns on portfolios increase monotonically with R&D intensity. In contrast, the high-minus-low $RDME$ portfolio in the Low illiquidity group generates a value-weighted average monthly return of only $-0.01\%$ ($t$-statistic = $-0.04$). The corresponding alphas relative to the FF3, FFC, and FF5 models are all negative and statistically insignificant at

[20] The Herfindahl-Hirschman Index is defined as $\text{HHI}_{j,t} = \sum_{i=1}^{N_j} s_{i,j,t}^2$, where $s_{i,j,t}$ is the market share of net sales (Compustat item SALE) of firm $i$ in industry $j$ in year $t$, $N_j$ is the number of firms in industry $j$ in year $t$, and $\text{HHI}_{j,t}$ is the Herfindahl-Hirschman Index of industry $j$ in year $t$. Small (large) values of HHI imply that the product market is shared by many competing firms (a few large firms). I compute HHI in every year and use the average value over the previous three years. This ensures that potential data errors do not have undue influence on my measure of product market competition. More details can be found in Hou and Robinson (2006).

conventional levels.

Examining the high competition subsample of the full sample, it can be seen that the high-minus-low $RDME$ portfolio in the High illiquidity group generates a value-weighted average monthly return of 1.75%, which is both economically large and statistically significant ($t$-statistic = 4.55). The average abnormal returns on the portfolio relative to the FF3, FFC, and FF5 models are, respectively, 1.77% ($t$-statistic = 4.42), 1.74% ($t$-statistic = 4.10), and 1.59% ($t$-statistic = 3.71) per month. The high-minus-low $RDME$ portfolio in the Low illiquidity group also generates a value-weighted average monthly return of 0.68% ($t$-statistic = 2.92). The monthly average abnormal returns on this portfolio relative to the FF3, FFC, and FF5 models are 0.52% ($t$-statistic = 2.27), 0.52% ($t$-statistic = 1.91), and 0.36% ($t$-statistic = 1.39), respectively. It is important to note that although an R&D premium exists in the Low illiquidity group, it is nearly three times smaller than that in the High illiquidity group. The value-weighted average abnormal returns on the high-minus-low $RDME$ portfolio are also about three times smaller than those in the High illiquidity group. These results, therefore, corroborate my finding that the positive R&D-return relation is much stronger among illiquid stocks.

Turning now to the low competition subsample of the all-but-microcaps sample, I observe that the high-minus-low $RDME$ portfolio in the High illiquidity group generates an equal-weighted average return of 0.77% per month, with a corresponding $t$-statistic of 2.18. The equal-weighted average monthly abnormal returns on the portfolio relative to the FF3, FFC, and FF5 models are 0.75% ($t$-statistic = 2.29), 0.68% ($t$-statistic = 2.00), and 1.01% ($t$-statistic = 3.18), respectively. The high-minus-low $RDME$ portfolio in the Low illiquidity group, however, generates an insignificant equal-weighted average monthly return of 0.06% ($t$-statistic = 0.43). The corresponding alphas relative to the FF3, FFC, and FF5 models are also very small and statistically insignificant. When the high competition subsample is examined, I notice that the equal-weighted average monthly return on the high-minus-low $RDME$ portfolio in the Low illiquidity group is 0.42% ($t$-statistic = 2.86). The monthly average abnormal returns of this difference portfolio relative to the FF3, FFC, and FF5 models are 0.63% ($t$-statistic = 3.69), 0.61% ($t$-statistic = 3.68), and 0.66% ($t$-statistic = 3.79), respectively. But the positive R&D-return relation in the High illiquidity group is much stronger than that of the Low illiquidity group. The high-minus-low $RDME$ portfolio generates an equal-weighted average monthly return of 0.84% ($t$-statistic = 3.19). The risk-adjusted monthly average returns of this portfolio relative to the FF3, FFC, and FF5 models are 0.85% ($t$-statistic = 3.11), 0.98% ($t$-statistic = 3.28), and 0.85% ($t$-statistic = 3.00),

respectively.

To summarize, the results in Table 2.7 reveal a more pronounced power of R&D intensity to predict returns in the high competition subsample, which is in line with Gu (2016). Moreover, product market competition cannot explain the important role that stock illiquidity plays in the positive relation between R&D intensity and future stock returns. Collectively, the results in Tables 2.5–2.7 suggest that stock-level illiquidity is an independent driver of the R&D premium.[21]

## 2.6 Conclusion

This chapter investigates the effect of illiquidity on the relation between R&D investment and expected equity returns. Based on a simple model of R&D venture, I develop a testable hypothesis that the positive R&D-return relation strengthens with level of stock illiquidity. An R&D firm lacking sufficient internal resources but wishing to continue the project issues outside financial claims to investors who may face liquidity problems before successful completion of the project. If the market is perfectly liquid and investors can sell their stocks instantaneously, then this would not matter much. However, in the presence of asymmetric information, investors or dealers who would be willing to buy such stocks might find it harder to decipher whether this sale is triggered by a cash constrained liquidity trader or by an informed trader selling upon receiving bad news about the R&D project. This results in further increases in the R&D premium to outside investors, which forces the firm to wrap up the project earlier, due to increased project costs (i.e., due to illiquidity) associated with external financing. Moreover, this illiquidity-induced reduction in project duration increases the likelihood of failure of the project due to its hurried completion. As a result, R&D-intensive firms' risk increases with their degree of stock illiquidity.

Consistent with my theoretical model's prediction, I find robust empirical evidence that the positive R&D-return relation exists among illiquid stocks. A further analysis indicates that the important role of illiquidity in the relation between R&D intensity and future stock

[21] One may also argue that my empirical results on the positive R&D-return relation are driven by return volatility rather than stock illiquidity. I address this concern in two complementary ways. First, I conduct the Fama and MacBeth (1973) cross-sectional regressions as in Table 2.2 after controlling for return volatility. More precisely, I run a monthly cross-sectional regression of illiquidity on a constant and volatility, and collect the residuals. Then at the end of each month $\tau$, stocks are sorted into three groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of (orthogonalized) illiquidity. In each month from July of year $t$ to June of year $t+1$ for the Low (High) orthogonalized illiquidity group formed in the previous month, I then run cross-sectional regressions specified by equation (2.5). Second, I perform trivariate-sort portfolio analyses as in Section 2.5.1 except that the first sort variable is stock return volatility. The results from these investigations, reported in the Appendix Tables 2.A24 and 2.A25, show that the positive R&D-return relation still strengthens with the level of stock illiquidity.

returns cannot be explained by factors such as financial constraints, innovation ability, and product market competition, which have been shown to affect the R&D premium in prior studies. All these results suggest that stock illiquidity is an independent driver of the positive R&D-return relation. This chapter thereby complements and extends the extant literature by providing an understanding of the R&D investment premium from the perspective of a firm's stock illiquidity.

Table 2.1: Summary statistics: Full sample

The sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a nonmissing research and development (R&D) intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. Panel A reports the time-series averages of the cross-sectional mean, standard deviation (SD), minimum, fifth percentile (5%), 25th percentile (25%), median, 75th percentile (75%), 95th percentile (95%), and maximum values of the distribution of each R&D intensity measure and illiquidity measure. $BAS$ is the average bid-ask spread, which is computed using one month's worth of daily data and requires a minimum of 15 valid daily observations. $RDME$ is computed at the end of June of each year $t$ using R&D expenditure at the end of the fiscal year ending in the calendar year $t-1$ scaled by $ME$ at the end of June of year $t$. $ME$ is the market value of equity (in million \$) computed as the number of shares outstanding times the absolute price of one share at the end of June of each year $t$. N is the number of firms in an average month. At the end of June of each year $t$, stocks are sorted into three portfolios using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $RDME$ computed at the end of June of year $t$ and the portfolios are rebalanced annually. Panel B, for each $RDME$-sorted portfolio, reports the time-series averages of the cross-sectional means for characteristics of constituent firms. $BM$ is the book-to-market ratio computed in June of each year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. At the end of each month $\tau$, stocks are also sorted into three portfolios using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $BAS$ in month $\tau$. Panel C reports both the value-weighted (VW) and equal-weighted (EW) average monthly excess returns (in %) for the portfolios sorted separately on $BAS$ and $RDME$. Panel D reports both VW and EW average monthly excess returns (in %) for quintile portfolios sorted separately on $BAS$ and $RDME$. H−L denotes the high-minus-low portfolio, that is, long stocks in the High portfolio and short stocks in the Low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016.

Panel A: Summary statistics of R&D intensity and illiquidity measures

| | Mean | SD | Minimum | 5% | 25% | Median | 75% | 95% | Maximum | N |
|---|---|---|---|---|---|---|---|---|---|---|
| $BAS$ | 0.06 | 0.06 | 0.00 | 0.02 | 0.03 | 0.04 | 0.07 | 0.17 | 0.67 | 2037 |
| $RDME$ | 0.07 | 0.14 | 0.00 | 0.00 | 0.01 | 0.03 | 0.07 | 0.25 | 2.88 | 2037 |

Panel B: Characteristics of portfolios sorted on $RDME$

| Portfolio | $BAS$ | $ME$ | $BM$ |
|---|---|---|---|
| Low | 0.061 | 2804.972 | 0.808 |
| Medium | 0.051 | 2979.094 | 0.624 |
| High | 0.072 | 662.931 | 0.928 |

Panel C: Portfolio excess returns

| | | Low | Medium | High | H−L |
|---|---|---|---|---|---|
| $BAS$ | VW | 0.69 | 0.72 | 0.41 | −0.28 |
| | | (3.85) | (2.32) | (0.85) | (−0.70) |
| | EW | 0.96 | 0.98 | 1.21 | 0.25 |
| | | (4.62) | (3.22) | (2.89) | (0.81) |
| $RDME$ | VW | 0.55 | 0.67 | 1.03 | 0.48 |
| | | (2.47) | (3.17) | (3.68) | (2.61) |
| | EW | 0.72 | 0.83 | 1.65 | 0.94 |
| | | (2.74) | (2.92) | (4.51) | (4.88) |

Panel D: Excess returns of quintile portfolios

| | | Low | 2 | 3 | 4 | High | H−L |
|---|---|---|---|---|---|---|---|
| $BAS$ | VW | 0.65 | 0.82 | 0.77 | 0.33 | 0.63 | −0.03 |
| | | (3.78) | (3.31) | (2.29) | (0.81) | (1.16) | (−0.05) |
| | EW | 0.94 | 1.02 | 1.02 | 0.80 | 1.44 | 0.50 |
| | | (4.82) | (4.11) | (3.31) | (2.22) | (3.18) | (1.37) |
| $RDME$ | VW | 0.70 | 0.53 | 0.71 | 0.83 | 1.01 | 0.31 |
| | | (2.91) | (2.48) | (3.17) | (3.31) | (3.37) | (1.41) |
| | EW | 0.82 | 0.55 | 0.87 | 1.12 | 1.86 | 1.04 |
| | | (3.09) | (2.03) | (3.01) | (3.52) | (4.78) | (4.47) |

Table 2.2: Cross-sectional regressions

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. At the end of each month $\tau$, stocks are sorted into three groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of illiquidity measured by the average bid-ask spread in month $\tau$. Then, in each month from July of year $t$ to June of year $t+1$ for the Low (High) illiquidity group formed in the previous month, I run a cross-sectional regression of monthly return on prior one-month return ($R_{1,1}$), prior year's return skipping the last month ($R_{12,2}$, i.e., return from month $\tau-12$ to month $\tau-2$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), and research and development (R&D) intensity measured by $RDME$ (i.e., R&D expenditure scaled by $ME$). In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity groups. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.1.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.90 | −4.02 | 0.56 | 0.10 | −0.05 | 0.95 |
| | (2.26) | (−8.79) | (2.98) | (1.27) | (−1.51) | (1.31) |
| High | 2.51 | −7.67 | −0.53 | 0.33 | −0.48 | 5.69 |
| | (4.19) | (−13.31) | (−1.52) | (3.47) | (−5.60) | (6.67) |
| High−Low | 1.62 | −3.65 | −1.09 | 0.24 | −0.43 | 4.74 |
| | (3.56) | (−5.68) | (−4.25) | (2.76) | (−4.90) | (6.00) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.67 | −5.66 | 0.18 | 0.03 | −0.09 | 0.28 |
| | (3.48) | (−9.35) | (0.80) | (0.41) | (−2.44) | (0.24) |
| High | 1.27 | −3.25 | 0.21 | 0.23 | −0.12 | 6.23 |
| | (1.87) | (−5.50) | (0.56) | (2.16) | (−1.69) | (3.29) |
| High−Low | −0.40 | 2.41 | 0.04 | 0.19 | −0.03 | 5.95 |
| | (−0.78) | (3.75) | (0.13) | (2.08) | (−0.48) | (3.48) |

Table 2.3: Cross-sectional regressions with illiquidity dummies

The table reports the time-series averages of the Fama and MacBeth (1973) cross-sectional regression coefficient estimates. At the end of each month $\tau$, dummy variables are created by sorting stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of illiquidity measured by the average bid-ask spread ($BAS$) in month $\tau$. Then, in each month from July of year $t$ to June of year $t+1$, I run a cross-sectional regression of monthly return on prior one-month return ($R_{1,1}$), prior year's return skipping the last month ($R_{12,2}$, i.e., return from month $\tau-12$ to month $\tau-2$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), research and development (R&D) intensity measured by $RDME$ (i.e., R&D expenditure scaled by $ME$), and illiquidity dummy (formed in the previous month) and interaction variables. $BAS_H$ ($BAS_L$) is a dummy variable equal to one for stocks in the High (Low) illiquidity group in a given month and is zero otherwise. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.1.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ | $RDME*BAS_H$ | $RDME*BAS_L$ | $BAS_H$ | $BAS_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.18 | −5.71 | 0.25 | 0.34 | −0.06 | 4.26 | | | | |
| (2.30) | (−12.72) | (1.08) | (3.61) | (−1.37) | (5.35) | | | | |
| 1.17 | −5.76 | 0.27 | 0.33 | −0.09 | 4.95 | | −5.03 | | 0.40 |
| (2.32) | (−12.87) | (1.21) | (3.86) | (−2.02) | (6.17) | | (−7.10) | | (2.77) |
| 1.51 | −5.94 | 0.25 | 0.31 | −0.10 | 2.30 | 4.07 | | −0.53 | |
| (3.43) | (−13.55) | (1.16) | (3.61) | (−2.48) | (2.92) | (5.73) | | (−2.89) | |
| 1.46 | −5.94 | 0.26 | 0.30 | −0.11 | 3.26 | 3.12 | −3.49 | −0.46 | 0.25 |
| (3.29) | (−13.50) | (1.27) | (3.77) | (−2.88) | (3.98) | (4.32) | (−5.37) | (−2.85) | (2.17) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.08 | −3.55 | 0.45 | 0.19 | −0.07 | 3.36 | | | | |
| (1.89) | (−6.82) | (1.58) | (1.79) | (−1.43) | (2.20) | | | | |
| 1.10 | −3.60 | 0.47 | 0.18 | −0.08 | 4.38 | | −4.98 | | 0.28 |
| (2.01) | (−7.07) | (1.68) | (1.83) | (−1.99) | (2.66) | | (−3.57) | | (2.25) |
| 1.34 | −3.74 | 0.49 | 0.13 | −0.10 | 1.78 | 5.08 | | −0.54 | |
| (2.68) | (−7.46) | (1.97) | (1.38) | (−2.47) | (1.66) | (3.58) | | (−2.99) | |
| 1.36 | −3.75 | 0.50 | 0.13 | −0.10 | 2.87 | 3.98 | −3.28 | −0.51 | 0.11 |
| (2.74) | (−7.53) | (2.01) | (1.43) | (−2.74) | (1.79) | (2.64) | (−2.41) | (−3.12) | (1.16) |

Table 2.4: Double sorts on illiquidity and R&D intensity

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity. Illiquidity is measured by the average bid-ask spread ($BAS$). R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. At the end of each month $\tau$, stocks are sorted into three groups using the breakpoints for the bottom 30% (Low (L)), middle 40% (Medium (M)), and top 30% (High (H)) of the ranked values of $BAS$ in month $\tau$. Independently, at the end of June of each year $t$, stocks are sorted into three groups using the breakpoints for the bottom 30% (L), middle 40% (M), and top 30% (H) of the ranked values of $RDME$ computed at the end of June of year $t$ and the stocks are held in the assigned groups for the subsequent 12 months. Nine portfolios are formed every month from the intersections of the illiquidity and R&D intensity groups. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.1.

| | Low illiquidity | | | | High illiquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.73 | 0.70 | 0.81 | 0.08 | −0.31 | 0.44 | 1.26 | 1.57 |
| | (3.84) | (3.89) | (3.32) | (0.51) | (−0.58) | (0.89) | (2.46) | (4.79) |
| FF3 $\alpha$ | 0.25 | 0.19 | 0.08 | −0.18 | −1.49 | −0.64 | 0.10 | 1.59 |
| | (2.87) | (2.97) | (0.54) | (−1.07) | (−5.28) | (−2.65) | (0.38) | (4.85) |
| FFC $\alpha$ | 0.21 | 0.22 | 0.14 | −0.08 | −0.74 | −0.09 | 0.62 | 1.36 |
| | (2.34) | (3.18) | (0.91) | (−0.46) | (−2.25) | (−0.36) | (2.12) | (3.50) |
| FF5 $\alpha$ | 0.12 | 0.02 | 0.00 | −0.12 | −0.72 | 0.07 | 0.75 | 1.47 |
| | (1.35) | (0.39) | (0.03) | (−0.72) | (−2.73) | (0.33) | (2.80) | (4.65) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.97 | 0.91 | 1.08 | 0.11 | 1.00 | 1.33 | 2.05 | 1.05 |
| | (4.73) | (4.51) | (4.70) | (1.09) | (2.60) | (3.41) | (4.76) | (3.80) |
| FF3 $\alpha$ | 0.35 | 0.24 | 0.36 | 0.00 | −0.01 | 0.40 | 1.02 | 1.03 |
| | (2.88) | (2.80) | (3.31) | (0.03) | (−0.08) | (2.34) | (4.38) | (3.73) |
| FFC $\alpha$ | 0.33 | 0.25 | 0.37 | 0.04 | 0.22 | 0.66 | 1.26 | 1.04 |
| | (2.82) | (3.03) | (3.50) | (0.41) | (1.42) | (3.88) | (5.68) | (3.86) |
| FF5 $\alpha$ | 0.08 | 0.01 | 0.17 | 0.09 | 0.38 | 0.90 | 1.51 | 1.12 |
| | (0.82) | (0.19) | (1.89) | (0.91) | (2.56) | (5.82) | (7.03) | (4.44) |

Table 2.5: Double sorts on illiquidity and R&D intensity after controlling for financial constraints

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity for both financially constrained and financially unconstrained subsamples. Financial constraint is measured by the KZ index developed in Kaplan and Zingales (1997). Illiquidity is measured by the average bid-ask spread. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates for portfolio analysis. At the end of June of each year $t$, I first assign stocks in the full sample to the financially constrained (unconstrained) subsample based on the median value of the distribution of the KZ index (i.e., financially constrained (unconstrained) subsample includes stocks above (below) the median). Then for each subsample, I conduct independent double sorts on illiquidity and R&D intensity as in Table 2.4. A similar procedure is followed for stocks in the all-but-microcaps sample. I report the value-weighted (equal-weighted) average monthly excess returns (in %) for portfolios based on the full sample (all-but-microcaps sample). The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Tables 2.1 and 2.4.

| | Full sample | | | | | | | | All-but-microcaps sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low illiquidity | | | | High illiquidity | | | | Low illiquidity | | | | High illiquidity | | | |
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Financially constrained subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.81 | 0.55 | 0.97 | 0.15 | 0.02 | 0.39 | 1.38 | 1.36 | 1.03 | 0.72 | 0.86 | −0.18 | 0.46 | 0.34 | 1.16 | 0.70 |
| | (3.57) | (2.57) | (2.90) | (0.55) | (0.03) | (0.72) | (2.29) | (3.00) | (4.05) | (2.98) | (3.29) | (−1.06) | (1.03) | (0.75) | (2.38) | (1.97) |
| FF3 $\alpha$ | 0.20 | −0.14 | 0.14 | −0.07 | −1.55 | −0.92 | 0.07 | 1.61 | 0.36 | 0.03 | 0.09 | −0.28 | −0.85 | −0.73 | −0.13 | 0.72 |
| | (1.37) | (−1.00) | (0.54) | (−0.24) | (−4.78) | (−2.84) | (0.20) | (3.90) | (2.28) | (0.19) | (0.55) | (−1.54) | (−3.28) | (−3.17) | (−0.50) | (2.08) |
| FFC $\alpha$ | 0.13 | −0.08 | 0.14 | 0.01 | −0.62 | −0.40 | 0.68 | 1.30 | 0.32 | 0.03 | 0.11 | −0.21 | −0.31 | −0.34 | 0.34 | 0.65 |
| | (0.89) | (−0.61) | (0.55) | (0.03) | (−1.44) | (−1.25) | (1.85) | (2.63) | (2.01) | (0.18) | (0.70) | (−1.19) | (−1.00) | (−1.44) | (1.24) | (1.70) |
| FF5 $\alpha$ | −0.07 | −0.28 | 0.12 | 0.19 | −1.25 | −0.33 | 0.62 | 1.87 | 0.08 | −0.21 | −0.15 | −0.22 | −0.80 | −0.28 | 0.12 | 0.93 |
| | (−0.46) | (−1.87) | (0.45) | (0.64) | (−3.46) | (−1.07) | (1.83) | (4.60) | (0.54) | (−1.52) | (−0.98) | (−1.21) | (−2.47) | (−1.08) | (0.47) | (2.68) |
| Panel B: Financially unconstrained subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.70 | 0.72 | 0.82 | 0.11 | 0.08 | 0.61 | 1.22 | 1.14 | 0.81 | 0.87 | 0.95 | 0.14 | 0.39 | 0.78 | 1.07 | 0.68 |
| | (3.76) | (3.73) | (3.35) | (0.60) | (0.18) | (1.28) | (2.63) | (3.08) | (4.25) | (4.42) | (4.33) | (1.47) | (1.06) | (2.03) | (2.71) | (3.09) |
| FF3 $\alpha$ | 0.25 | 0.21 | 0.17 | −0.08 | −0.79 | −0.37 | 0.22 | 1.00 | 0.24 | 0.22 | 0.27 | 0.03 | −0.49 | −0.07 | 0.13 | 0.62 |
| | (2.75) | (2.44) | (0.98) | (−0.44) | (−2.97) | (−1.29) | (0.76) | (2.67) | (2.17) | (2.59) | (2.30) | (0.36) | (−3.08) | (−0.36) | (0.64) | (2.83) |
| FFC $\alpha$ | 0.18 | 0.23 | 0.26 | 0.08 | −0.45 | 0.16 | 0.64 | 1.08 | 0.23 | 0.23 | 0.32 | 0.09 | −0.18 | 0.26 | 0.51 | 0.69 |
| | (2.06) | (2.32) | (1.54) | (0.45) | (−1.64) | (0.57) | (2.06) | (2.77) | (2.19) | (2.89) | (2.67) | (1.02) | (−1.15) | (1.39) | (2.36) | (3.15) |
| FF5 $\alpha$ | 0.05 | −0.03 | 0.12 | 0.08 | −0.32 | 0.29 | 0.88 | 1.21 | −0.04 | 0.01 | 0.08 | 0.12 | −0.06 | 0.42 | 0.72 | 0.79 |
| | (0.53) | (−0.32) | (0.71) | (0.38) | (−1.22) | (1.09) | (2.96) | (3.19) | (−0.44) | (0.17) | (0.78) | (1.30) | (−0.35) | (2.31) | (3.45) | (3.85) |

## Table 2.6: Double sorts on illiquidity and R&D intensity after controlling for innovation ability

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity for both low innovation ability and high innovation ability subsamples. Following Cohen, Diether, and Malloy (2013), innovation ability is computed as the average of the slope coefficient estimates from the time-series regressions of sales growth on past six years of R&D investments. Illiquidity is measured by the average bid-ask spread. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed non-financial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates for portfolio analysis. At the end of June of each year $t$, I first assign stocks in the full sample to the low (high) innovation ability subsample based on the median value of the distribution of the innovation ability (i.e., low (high) innovation ability subsample includes stocks below (above) the median). Then for each subsample, I conduct independent double sorts on illiquidity and R&D intensity as in Table 2.4. A similar procedure is followed for stocks in the all-but-microcaps sample. I report the value-weighted (equal-weighted) average monthly excess returns (in %) for portfolios based on the full sample (all-but-microcaps sample). The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Tables 2.1 and 2.4.

| | Full sample | | | | | | | | All-but-microcaps sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low illiquidity | | | | High illiquidity | | | | Low illiquidity | | | | High illiquidity | | | |
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Low innovation ability subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.79 | 0.92 | 1.15 | 0.36 | 0.55 | 1.44 | 1.25 | 0.70 | 0.91 | 1.04 | 1.11 | 0.21 | 0.70 | 1.00 | 1.21 | 0.51 |
| | (3.79) | (3.42) | (3.77) | (1.41) | (1.11) | (2.99) | (2.57) | (1.75) | (3.68) | (4.44) | (3.67) | (1.31) | (1.70) | (2.49) | (2.69) | (1.80) |
| FF3 $\alpha$ | 0.22 | 0.27 | 0.48 | 0.25 | −0.43 | 0.47 | 0.23 | 0.66 | 0.24 | 0.33 | 0.41 | 0.17 | −0.25 | 0.08 | 0.29 | 0.54 |
| | (1.93) | (1.56) | (2.01) | (1.00) | (−1.48) | (1.69) | (0.72) | (1.66) | (1.75) | (2.52) | (2.25) | (1.11) | (−1.25) | (0.42) | (1.19) | (1.96) |
| FFC $\alpha$ | 0.17 | 0.30 | 0.46 | 0.29 | −0.09 | 0.85 | 0.64 | 0.73 | 0.24 | 0.38 | 0.42 | 0.17 | 0.01 | 0.38 | 0.58 | 0.57 |
| | (1.60) | (1.72) | (1.96) | (1.18) | (−0.29) | (3.04) | (1.92) | (1.59) | (1.86) | (2.95) | (2.29) | (1.12) | (0.06) | (1.94) | (2.39) | (2.16) |
| FF5 $\alpha$ | 0.09 | −0.01 | 0.33 | 0.23 | −0.03 | 0.97 | 0.75 | 0.78 | −0.01 | 0.13 | 0.20 | 0.21 | 0.01 | 0.51 | 0.76 | 0.75 |
| | (0.74) | (−0.04) | (1.51) | (0.95) | (−0.10) | (3.31) | (2.47) | (1.81) | (−0.08) | (1.11) | (1.31) | (1.43) | (0.05) | (2.50) | (3.46) | (2.53) |
| Panel B: High innovation ability subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.75 | 0.60 | 1.07 | 0.32 | 0.55 | 1.08 | 1.36 | 0.81 | 0.90 | 0.86 | 0.99 | 0.09 | 0.66 | 0.88 | 1.36 | 0.70 |
| | (3.55) | (2.57) | (3.81) | (1.53) | (1.30) | (2.31) | (2.65) | (1.97) | (4.37) | (3.78) | (3.61) | (0.58) | (1.69) | (2.27) | (3.02) | (3.00) |
| FF3 $\alpha$ | 0.19 | −0.02 | 0.38 | 0.19 | −0.29 | 0.04 | 0.23 | 0.52 | 0.30 | 0.17 | 0.26 | −0.05 | −0.25 | −0.07 | 0.34 | 0.58 |
| | (1.36) | (−0.13) | (1.84) | (0.91) | (−0.94) | (0.12) | (0.75) | (1.32) | (2.65) | (1.57) | (1.64) | (−0.32) | (−1.34) | (−0.42) | (1.59) | (2.65) |
| FFC $\alpha$ | 0.13 | −0.01 | 0.38 | 0.25 | −0.02 | 0.45 | 0.57 | 0.59 | 0.31 | 0.22 | 0.29 | −0.02 | 0.05 | 0.22 | 0.64 | 0.59 |
| | (0.88) | (−0.10) | (1.81) | (1.24) | (−0.05) | (1.47) | (1.91) | (1.72) | (2.88) | (2.17) | (1.81) | (−0.14) | (0.26) | (1.41) | (3.07) | (2.72) |
| FF5 $\alpha$ | −0.14 | −0.31 | 0.18 | 0.32 | −0.06 | 0.41 | 0.60 | 0.66 | 0.05 | −0.02 | 0.11 | 0.06 | 0.14 | 0.28 | 0.58 | 0.44 |
| | (−1.09) | (−2.38) | (0.97) | (1.48) | (−0.21) | (1.31) | (1.86) | (1.68) | (0.49) | (−0.22) | (0.77) | (0.46) | (0.69) | (1.46) | (2.77) | (1.89) |

## Table 2.7: Double sorts on illiquidity and R&D intensity after controlling for product market competition

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity for both low competition and high competition subsamples. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) as in Hou and Robinson (2006). Illiquidity is measured by the average bid-ask spread. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates for portfolio analysis. At the end of June of each year $t$, I first assign stocks in the full sample to the low (high) competition subsample based on the median value of the distribution of HHI (i.e., low (high) competition subsample includes stocks above (below) the median). Then for each subsample, I conduct independent double sorts on illiquidity and R&D intensity as in Table 2.4. A similar procedure is followed for stocks in the all-but-microcaps sample. I report the value-weighted (equal-weighted) average monthly excess returns (in %) for portfolios based on the full sample (all-but-microcaps sample). The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Tables 2.1 and 2.4.

| | Full sample | | | | | | | | All-but-microcaps sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low illiquidity | | | | High illiquidity | | | | Low illiquidity | | | | High illiquidity | | | |
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Low competition subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.72 | 0.64 | 0.71 | −0.01 | −0.49 | 0.43 | 1.19 | 1.69 | 0.73 | 0.80 | 0.79 | 0.06 | 0.71 | 0.65 | 1.48 | 0.77 |
| | (3.74) | (3.20) | (2.90) | (−0.04) | (−0.87) | (0.84) | (2.19) | (3.90) | (3.01) | (3.58) | (2.82) | (0.43) | (1.43) | (1.33) | (2.69) | (2.18) |
| FF3 $\alpha$ | 0.25 | 0.09 | −0.06 | −0.31 | −1.79 | −0.68 | −0.11 | 1.68 | 0.16 | 0.21 | 0.07 | −0.09 | −0.44 | −0.40 | 0.31 | 0.75 |
| | (2.21) | (0.82) | (−0.40) | (−1.67) | (−5.77) | (−2.37) | (−0.36) | (4.02) | (1.06) | (1.66) | (0.51) | (−0.66) | (−1.78) | (−2.21) | (1.28) | (2.29) |
| FFC $\alpha$ | 0.16 | 0.11 | 0.01 | −0.15 | −1.06 | −0.20 | 0.41 | 1.48 | 0.16 | 0.24 | 0.17 | 0.01 | 0.11 | −0.04 | 0.79 | 0.68 |
| | (1.30) | (1.04) | (0.08) | (−0.83) | (−2.76) | (−0.72) | (1.27) | (2.89) | (1.01) | (2.08) | (1.31) | (0.08) | (0.39) | (−0.20) | (3.25) | (2.00) |
| FF5 $\alpha$ | 0.06 | −0.20 | −0.20 | −0.26 | −1.25 | −0.11 | 0.48 | 1.74 | −0.12 | −0.05 | −0.11 | 0.01 | −0.36 | −0.01 | 0.65 | 1.01 |
| | (0.47) | (−2.06) | (−1.44) | (−1.32) | (−4.17) | (−0.39) | (1.56) | (4.16) | (−0.95) | (−0.43) | (−0.93) | (0.08) | (−1.16) | (−0.05) | (2.52) | (3.18) |
| Panel B: High competition subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.63 | 0.95 | 1.32 | 0.68 | −0.26 | 0.44 | 1.50 | 1.75 | 0.71 | 0.86 | 1.14 | 0.42 | 0.32 | 0.94 | 1.16 | 0.84 |
| | (2.88) | (4.73) | (4.75) | (2.92) | (−0.44) | (0.83) | (2.73) | (4.55) | (3.13) | (3.98) | (5.74) | (2.86) | (0.59) | (1.73) | (2.03) | (3.19) |
| FF3 $\alpha$ | 0.17 | 0.45 | 0.69 | 0.52 | −1.30 | −0.58 | 0.48 | 1.77 | 0.15 | 0.31 | 0.78 | 0.63 | −0.69 | 0.06 | 0.16 | 0.85 |
| | (1.28) | (4.82) | (3.78) | (2.27) | (−3.68) | (−1.97) | (1.52) | (4.42) | (1.16) | (2.90) | (5.14) | (3.69) | (−3.58) | (0.24) | (0.62) | (3.11) |
| FFC $\alpha$ | 0.25 | 0.49 | 0.77 | 0.52 | −0.66 | 0.01 | 1.08 | 1.74 | 0.21 | 0.34 | 0.81 | 0.61 | −0.31 | 0.46 | 0.67 | 0.98 |
| | (1.42) | (5.01) | (4.08) | (1.91) | (−1.68) | (0.03) | (3.20) | (4.10) | (1.58) | (3.11) | (4.95) | (3.68) | (−1.41) | (1.63) | (2.16) | (3.28) |
| FF5 $\alpha$ | 0.26 | 0.34 | 0.62 | 0.36 | −0.28 | 0.24 | 1.31 | 1.59 | −0.01 | 0.16 | 0.65 | 0.66 | −0.07 | 0.73 | 0.78 | 0.85 |
| | (1.62) | (3.18) | (3.19) | (1.39) | (−0.80) | (0.73) | (3.84) | (3.71) | (−0.10) | (1.66) | (4.57) | (3.79) | (−0.35) | (2.57) | (2.56) | (3.00) |

## Appendix

The transformed optimization program with the Lagrange multiplier can be written as

$$\max_{\{m_t\},\lambda,T} \pi = \alpha F(T) e^{-rT} X - \frac{\int_0^T m_t e^{-rt} dt}{\mu} + \lambda \left[ \int_0^T h(m_t) dt - D \right], \tag{2.A1}$$

where

$$F(T) = \frac{T + \int_0^T h(m_t) dt}{\overline{T}}.$$

First-order conditions:

With respect to $\{m_t\}$:

$$\left[ \frac{\alpha e^{-rT} X}{\overline{T}} + \lambda \right] h'(m_t) = \frac{e^{-rt}}{\mu}, \tag{2.A2}$$

with respect to $\lambda$:

$$\int_0^T h(m_t) dt - D = 0. \tag{2.A3}$$

Solving the above two equations, I can find $\lambda^*(T, D)$ and $m_t^*(T, D)$. Inserting them in the objective function gives the optimal value of profit, denoted $\pi^*(T, D)$. Setting $\frac{d[\pi^*(T,D)]}{dT} = 0$, I get

$$\left[ \frac{\alpha e^{-rT} X}{\overline{T}} + \lambda \right] h(m_T) - \frac{m_T e^{-rT}}{\mu} - \frac{r e^{-rT} X}{\overline{T}} = 0. \tag{2.A4}$$

I combine all the first-order conditions to get the following results.

*Result 1*: $\frac{dT^*}{d\mu} > 0$, implying increased illiquidity (a lower value of $\mu$) will reduce the terminal date for the R&D project completion. That is, the project will be completed at an earlier date.

The proof is obtained by implicitly differentiating (A4), which gets us

$$\frac{dT^*}{d\mu} = -\frac{\pi^*_{\mu T^*}(T^*, \mu)}{\pi^*_{T^* T^*}(T^*, \mu)} > 0,$$

where the subscripts refer to the partial derivatives with respect to the relevant variables calculated at the optimum value of $T^*$. The result follows since $\pi^*_{T^* T^*}(T^*, \mu) < 0$ due to the second-order condition for the optimum and $\pi^*_{\mu T^*}(T^*, \mu) = \frac{m_T e^{-rT^*}}{\mu^2} > 0$.

*Result 2*: The probability of project success increases (decreases) with the liquidity (illiquidity) of the stock.

The proof is obtained by differentiating the cumulative probability distribution function

of project success,

$$F(T) = \frac{T + \int_0^T h(m_t)dt}{\overline{T}},$$

with respect to $\mu$ and by the use of *Result 1*, and is given below:

$$F'(T^*)\frac{dT^*}{d\mu} = \left[\frac{1 + h(m_T)}{\overline{T}}\right]\frac{dT^*}{d\mu} > 0,$$

as *Result 1* shows that $\frac{dT^*}{d\mu} > 0$.

*Result 3*: The magnitude of external finance raised from the stock market increases with the level of illiquidity.

Proof: For the sake of exposition and a closed-form solution, I work with a specific function for the proof of *Result 3*. Specifically, I adopt a simple specification of the following function:

$$h(m_t) = m_t^{1/2}.$$

First-order conditions (A2) and (A3) can be written as

$$\frac{\left[\frac{\alpha e^{-rT}X}{\overline{T}} + \lambda\right]}{2} m_t^{-1/2} = \frac{e^{-rt}}{\mu},$$

or

$$\mu\frac{\left[\frac{\alpha e^{-rT}X}{\overline{T}} + \lambda\right]}{2} e^{rt} = m_t^{1/2}, \tag{2.A2$'$}$$

$$\int_0^T m_t^{1/2}dt - D = 0. \tag{2.A3$'$}$$

Substituting (A2$'$) into (A3$'$), I get $\mu\frac{\left[\frac{\alpha e^{-rT}X}{\overline{T}} + \lambda\right]}{2}\int_0^T e^{rt}dt = D$ or $\mu\frac{\left[\frac{\alpha e^{-rT}X}{\overline{T}} + \lambda\right]}{2r}(e^{rT} - 1) = D$ and simplifying yields $\mu\frac{\left[\frac{\alpha e^{-rT}X}{\overline{T}} + \lambda\right]}{2} = \frac{rD}{(e^{rT}-1)}$. Then from (A2$'$), I get $m_t = \left(\frac{rD}{e^{rT}-1}\right)^2\left(\frac{1}{e^{-rt}}\right)^2$. The present value of total amount of external finance is therefore

$$Z = \int_0^T m_t e^{-rt}dt = \left(\frac{rD}{e^{rT}-1}\right)^2\int_0^T e^{rt}dt = \frac{rD^2}{e^{rT}-1}.$$

$$\frac{dZ}{d\mu} = -\left(\frac{rD}{e^{rT}-1}\right)^2 e^{rT}\frac{dT^*}{d\mu} < 0. \quad Q.E.D.$$

Proof of hypothesis: The discounted value of the return $e^{-rT}R = \frac{\int_0^T m_t e^{-rt} dt}{F(T)\alpha\mu}$ is a decreasing function of $\mu$.

*Result 3* shows that $Z = \int_0^T m_t e^{-rt} dt$ decreases with $\mu$, *Result 2* establishes that $F(T)$ increases with $\mu$, and both results are achieved via *Result 1*, which states that $\frac{dT^*}{d\mu} > 0$. *Q.E.D.*

Table 2.A1: Summary statistics: Preliminary sample

The table reports the time-series averages of the cross-sectional mean, standard deviation (SD), minimum, fifth percentile (5%), 25th percentile (25%), median, 75th percentile (75%), 95th percentile (95%), and maximum values of the distribution of each variable. The sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks with a positive book value of equity. $BAS$ is the average bid-ask spread and $ILLIQ$ is the Amihud (2002) illiquidity measure, both of which are computed using one month's worth of daily data and require a minimum of 15 valid daily observations. N is the number of firms in the average month. $ME$ is the market value of equity (in million \$) computed as the number of shares outstanding times the price of one share at the end of June of each year $t$. $RDME$ is computed at the end of June of each year $t$ using research and development (R&D) expenditure at the end of the fiscal year ending in the calendar year $t-1$ scaled by $ME$ at the end of June of year $t$. $RDAT$ is computed in June of each year $t$ using R&D expenditure scaled by total assets ($AT$) at the end of the fiscal year ending in the calendar year $t-1$. $BM$ is the book-to-market ratio computed in June of each year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. The sample period is from January 1975 to December 2016.

| | Mean | SD | Minimum | 5% | 25% | Median | 75% | 95% | Maximum | N |
|---|---|---|---|---|---|---|---|---|---|---|
| $BAS$ | 0.06 | 0.07 | 0.00 | 0.01 | 0.03 | 0.04 | 0.07 | 0.19 | 0.76 | 3964 |
| $ILLIQ$ | 4.76 | 41.55 | 0.00 | 0.00 | 0.02 | 0.15 | 1.19 | 16.30 | 1813.44 | 3144 |
| $RDME$ | 0.07 | 0.18 | 0.00 | 0.00 | 0.01 | 0.03 | 0.07 | 0.26 | 4.89 | 2121 |
| $RDAT$ | 0.08 | 0.14 | 0.00 | 0.00 | 0.01 | 0.04 | 0.10 | 0.29 | 2.82 | 2128 |
| $ME$ | 1821.07 | 8713.36 | 0.58 | 8.16 | 48.24 | 194.20 | 796.98 | 6882.98 | 231282.17 | 4137 |
| $BM$ | 0.89 | 1.32 | 0.00 | 0.13 | 0.37 | 0.66 | 1.09 | 2.22 | 43.28 | 3751 |

Table 2.A2: Summary statistics: All-but-microcaps sample

The all-but-microcaps sample excludes stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution and retains the remaining NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks with both nonmissing research and development (R&D) intensity and valid illiquidity estimates. Panel A reports the time-series averages of the cross-sectional mean, standard deviation (SD), minimum, fifth percentile (5%), 25th percentile (25%), median, 75th percentile (75%), 95th percentile (95%), and maximum values of the distribution of each R&D intensity measure and illiquidity measure. $BAS$ is the average bid-ask spread, which is computed using one month's worth of daily data and requires a minimum of 15 valid daily observations. $RDME$ is computed at the end of June of each year $t$ using R&D expenditure at the end of the fiscal year ending in the calendar year $t-1$ scaled by $ME$ at the end of June of year $t$. $ME$ is the market value of equity (in million \$) computed as the number of shares outstanding times the price of one share at the end of June of each year $t$. N is the number of firms in an average month. At the end of June of each year $t$, stocks are sorted into three portfolios using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $RDME$ computed at the end of June of year $t$ and the portfolios are rebalanced annually. Panel B, for each $RDME$-sorted portfolio, reports the time-series averages of the cross-sectional means for characteristics of constituent firms. $BM$ is the book-to-market ratio computed in June of each year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. At the end of each month $\tau$, stocks are also sorted into three portfolios using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $BAS$ in month $\tau$. Panel C reports both the value-weighted (VW) and equal-weighted (EW) average monthly excess returns (in %) for the portfolios sorted separately on $BAS$ and $RDME$. Panel D reports both VW and EW average monthly excess returns (in %) for quintile portfolios sorted separately on $BAS$ and $RDME$. H−L denotes the high-minus-low portfolio, that is, long stocks in the High portfolio and short stocks in the Low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016.

Panel A: Summary statistics of R&D intensity and illiquidity measures

| | Mean | SD | Minimum | 5% | 25% | Median | 75% | 95% | Maximum | N |
|---|---|---|---|---|---|---|---|---|---|---|
| $BAS$ | 0.03 | 0.02 | 0.00 | 0.01 | 0.02 | 0.03 | 0.04 | 0.06 | 0.14 | 805 |
| $RDME$ | 0.03 | 0.05 | 0.00 | 0.00 | 0.01 | 0.02 | 0.04 | 0.12 | 0.61 | 805 |

Panel B: Characteristics of portfolios sorted on $RDME$

| Portfolio | $BAS$ | $ME$ | $BM$ |
|---|---|---|---|
| Low | 0.032 | 5257.516 | 0.538 |
| Medium | 0.031 | 5558.617 | 0.521 |
| High | 0.035 | 4222.950 | 0.678 |

Panel C: Portfolio excess returns

| | | Low | Medium | High | H−L |
|---|---|---|---|---|---|
| $BAS$ | VW | 0.64 | 0.71 | 0.59 | −0.06 |
| | | (3.73) | (2.84) | (1.45) | (−0.18) |
| | EW | 0.89 | 0.93 | 0.72 | −0.18 |
| | | (4.59) | (3.58) | (1.72) | (−0.59) |
| $RDME$ | VW | 0.50 | 0.66 | 0.87 | 0.36 |
| | | (2.29) | (3.18) | (3.50) | (2.37) |
| | EW | 0.69 | 0.78 | 1.11 | 0.42 |
| | | (2.64) | (2.90) | (3.53) | (2.73) |

Panel D: Excess returns of quintile portfolios

| | | Low | 2 | 3 | 4 | High | H−L |
|---|---|---|---|---|---|---|---|
| $BAS$ | VW | 0.59 | 0.73 | 0.78 | 0.79 | 0.50 | −0.09 |
| | | (3.54) | (3.40) | (2.97) | (2.35) | (1.11) | (−0.23) |
| | EW | 0.86 | 0.90 | 0.97 | 0.93 | 0.61 | −0.25 |
| | | (4.61) | (4.11) | (3.70) | (2.85) | (1.34) | (−0.70) |
| $RDME$ | VW | 0.61 | 0.49 | 0.72 | 0.66 | 0.90 | 0.29 |
| | | (2.49) | (2.28) | (3.40) | (2.81) | (3.43) | (1.57) |
| | EW | 0.76 | 0.62 | 0.77 | 0.90 | 1.20 | 0.44 |
| | | (2.80) | (2.33) | (2.87) | (3.16) | (3.61) | (2.29) |

Table 2.A3: Cross-sectional regressions with industry dummies

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the regressions include industry dummies as additional controls, which are based on the Fama and French 12-industry classification scheme. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.94 | −4.53 | 0.61 | 0.12 | −0.05 | 1.06 |
| | (2.33) | (−10.17) | (3.55) | (1.81) | (−1.52) | (1.64) |
| High | 2.29 | −7.94 | −0.33 | 0.41 | −0.47 | 4.86 |
| | (3.68) | (−13.78) | (−1.09) | (4.66) | (−5.35) | (6.54) |
| High−Low | 1.35 | −3.41 | −0.94 | 0.29 | −0.42 | 3.79 |
| | (2.74) | (−5.52) | (−4.10) | (3.38) | (−4.71) | (4.54) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.69 | −6.19 | 0.28 | 0.06 | −0.10 | 0.29 |
| | (3.53) | (−10.34) | (1.43) | (0.78) | (−2.53) | (0.27) |
| High | 0.91 | −3.70 | 0.21 | 0.28 | −0.12 | 4.17 |
| | (1.33) | (−6.24) | (0.61) | (3.00) | (−1.61) | (2.56) |
| High−Low | −0.78 | 2.48 | −0.07 | 0.22 | −0.02 | 3.88 |
| | (−1.39) | (3.94) | (−0.24) | (2.45) | (−0.31) | (2.37) |

Table 2.A4: Cross-sectional regressions: Extended sample period

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the sample period begins in January 1963 and ends in December 2016. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 1.03 | −4.00 | 0.56 | 0.13 | −0.06 | 1.09 |
| | (2.61) | (−8.21) | (3.13) | (1.64) | (−1.72) | (1.55) |
| High | 3.00 | −7.61 | −0.62 | 0.36 | −0.51 | 4.86 |
| | (5.11) | (−12.70) | (−1.83) | (3.84) | (−6.20) | (5.73) |
| High−Low | 1.97 | −3.61 | −1.17 | 0.23 | −0.45 | 3.76 |
| | (4.55) | (−5.54) | (−4.57) | (2.84) | (−5.43) | (4.69) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.77 | −5.63 | 0.18 | 0.09 | −0.09 | 1.12 |
| | (3.75) | (−8.70) | (0.84) | (1.11) | (−2.56) | (1.01) |
| High | 1.01 | −3.31 | 0.12 | 0.21 | −0.06 | 6.13 |
| | (1.54) | (−5.74) | (0.34) | (2.09) | (−0.83) | (3.43) |
| High−Low | −0.75 | 2.33 | −0.06 | 0.12 | 0.04 | 5.01 |
| | (−1.51) | (3.71) | (−0.20) | (1.22) | (0.56) | (3.16) |

Table 2.A5: Cross-sectional regressions: Returns adjusted for delistings

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the returns are adjusted following Shumway (1997) for delistings. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.92 | −3.91 | 0.54 | 0.10 | −0.05 | 0.83 |
| | (2.34) | (−8.67) | (2.91) | (1.29) | (−1.49) | (1.17) |
| High | 1.92 | −7.17 | −0.30 | 0.36 | −0.39 | 5.35 |
| | (3.26) | (−12.50) | (−0.93) | (3.76) | (−4.45) | (6.32) |
| High−Low | 1.01 | −3.25 | −0.83 | 0.26 | −0.34 | 4.52 |
| | (2.23) | (−5.06) | (−3.56) | (3.11) | (−3.83) | (5.76) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.64 | −5.56 | 0.21 | 0.04 | −0.09 | 0.20 |
| | (3.41) | (−9.14) | (0.94) | (0.45) | (−2.48) | (0.17) |
| High | 1.25 | −3.18 | 0.24 | 0.22 | −0.13 | 6.18 |
| | (1.84) | (−5.35) | (0.64) | (2.11) | (−1.72) | (3.25) |
| High−Low | −0.38 | 2.38 | 0.03 | 0.19 | −0.03 | 5.99 |
| | (−0.74) | (3.71) | (0.11) | (1.99) | (−0.50) | (3.55) |

Table 2.A6: Cross-sectional regressions: 1975–2000

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the sample period begins in January 1975 and ends in December 2000. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.43 | −4.45 | 1.03 | 0.09 | −0.05 | 1.61 |
| | (0.93) | (−7.61) | (5.97) | (0.79) | (−0.94) | (1.60) |
| High | 2.88 | −9.47 | −0.02 | 0.30 | −0.71 | 7.13 |
| | (4.03) | (−17.12) | (−0.10) | (2.26) | (−6.99) | (6.10) |
| High−Low | 2.45 | −5.02 | −1.06 | 0.21 | −0.66 | 5.52 |
| | (4.17) | (−7.67) | (−4.75) | (1.83) | (−6.30) | (5.14) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 0.80 | −6.43 | 0.74 | 0.04 | −0.05 | 0.49 |
| | (1.38) | (−9.09) | (2.95) | (0.36) | (−0.93) | (0.31) |
| High | 0.03 | −3.67 | 1.18 | 0.35 | −0.03 | 5.92 |
| | (0.04) | (−4.82) | (5.19) | (2.39) | (−0.35) | (2.28) |
| High−Low | −0.77 | 2.76 | 0.44 | 0.30 | 0.02 | 5.43 |
| | (−1.19) | (3.22) | (1.78) | (2.30) | (0.22) | (2.46) |

Table 2.A7: Cross-sectional regressions: 2002–2016

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the sample period begins in January 2002 and ends in December 2016. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 1.28 | −2.50 | −0.17 | 0.03 | −0.02 | −0.42 |
| | (1.66) | (−3.18) | (−0.41) | (0.36) | (−0.61) | (−0.38) |
| High | 0.93 | −3.74 | −1.26 | 0.34 | −0.01 | 2.89 |
| | (0.81) | (−3.92) | (−1.39) | (2.23) | (−0.09) | (2.40) |
| High−Low | −0.34 | −1.23 | −1.09 | 0.31 | 0.01 | 3.30 |
| | (−0.45) | (−0.98) | (−1.73) | (2.05) | (0.05) | (2.63) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 2.51 | −2.81 | −0.58 | 0.00 | −0.10 | −0.87 |
| | (3.15) | (−2.67) | (−1.40) | (−0.04) | (−2.58) | (−0.44) |
| High | 2.54 | −1.38 | −0.86 | 0.04 | −0.19 | 4.90 |
| | (1.90) | (−1.38) | (−0.89) | (0.28) | (−1.56) | (1.99) |
| High−Low | 0.03 | 1.42 | −0.28 | 0.04 | −0.09 | 5.77 |
| | (0.03) | (1.26) | (−0.41) | (0.33) | (−0.73) | (1.97) |

Table 2.A8: Cross-sectional regressions: High-tech and low-tech firms

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity. Following Chan, Martin, and Kensinger (1990), I partition the full sample (all-but-microcaps sample) into high-tech firms and low-tech firms based on the Fama and French 12 industry group classification system. The high-tech group includes firms in the Consumer Durables, Business Equipment, Healthcare, and Telecommunications industries, while the low-tech group includes firms in the Consumer Nondurables, Chemical and Allied Products, Energy, Manufacturing, Utilities, Wholesale and Retail, and Other industries. Panels A and B (Panels C and D) report results for high-tech and low-tech firms in the full sample (all-but-microcaps sample), respectively. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: High-tech firms in full sample | | | | | | |
| Low | 1.13 | −4.34 | 0.59 | 0.14 | −0.06 | 1.07 |
| | (2.66) | (−7.62) | (3.16) | (1.26) | (−1.51) | (1.29) |
| High | 3.18 | −8.32 | −0.82 | 0.34 | −0.51 | 3.74 |
| | (4.52) | (−12.65) | (−2.28) | (3.13) | (−4.77) | (4.38) |
| High−Low | 2.05 | −3.98 | −1.42 | 0.20 | −0.45 | 2.67 |
| | (3.47) | (−5.15) | (−4.51) | (1.60) | (−4.12) | (2.59) |
| Panel B: Low-tech firms in full sample | | | | | | |
| Low | 0.82 | −4.36 | 0.52 | 0.13 | −0.04 | 0.71 |
| | (1.91) | (−7.39) | (2.44) | (1.94) | (−1.22) | (0.84) |
| High | 2.19 | −6.91 | −0.28 | 0.46 | −0.46 | 7.06 |
| | (3.60) | (−10.47) | (−0.73) | (3.71) | (−5.73) | (4.70) |
| High−Low | 1.37 | −2.55 | −0.81 | 0.33 | −0.42 | 6.35 |
| | (3.06) | (−3.43) | (−2.89) | (2.73) | (−5.07) | (4.54) |
| Panel C: High-tech firms in all-but-microcaps sample | | | | | | |
| Low | 1.64 | −5.05 | 0.11 | −0.01 | −0.07 | 0.84 |
| | (3.17) | (−6.19) | (0.41) | (−0.09) | (−1.59) | (0.51) |
| High | 1.84 | −3.39 | 0.13 | 0.24 | −0.20 | 4.16 |
| | (2.20) | (−4.56) | (0.35) | (1.72) | (−1.91) | (2.23) |
| High−Low | 0.20 | 1.66 | 0.02 | 0.25 | −0.12 | 3.31 |
| | (0.25) | (1.74) | (0.06) | (1.80) | (−1.27) | (1.69) |
| Panel D: Low-tech firms in all-but-microcaps sample | | | | | | |
| Low | 1.37 | −5.50 | 0.18 | 0.12 | −0.05 | −2.05 |
| | (2.76) | (−7.87) | (0.75) | (1.39) | (−1.33) | (−0.97) |
| High | 1.19 | −3.02 | 0.25 | 0.41 | −0.07 | 3.71 |
| | (1.55) | (−4.27) | (0.52) | (3.17) | (−0.94) | (1.14) |
| High−Low | −0.18 | 2.48 | 0.07 | 0.29 | −0.02 | 5.76 |
| | (−0.28) | (3.01) | (0.16) | (2.17) | (−0.26) | (1.73) |

Table 2.A9: Cross-sectional regressions: Illiquidity computed using 12-month data

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that a stock's illiquidity (proxied by the average bid-ask spread) in month $\tau$ is computed using one year's worth of daily data covering the 12-month period including months $\tau-11$ through $\tau$, inclusive, and requires a minimum of 200 valid daily observations. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.73 | −4.53 | 0.71 | 0.11 | −0.04 | 0.67 |
| | (1.85) | (−9.45) | (3.69) | (1.50) | (−1.35) | (0.97) |
| High | 2.57 | −7.37 | −0.23 | 0.35 | −0.47 | 5.43 |
| | (4.23) | (−13.21) | (−0.90) | (3.78) | (−5.43) | (6.74) |
| High−Low | 1.84 | −2.84 | −0.95 | 0.24 | −0.42 | 4.76 |
| | (3.78) | (−4.62) | (−5.01) | (2.60) | (−4.66) | (6.10) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.58 | −4.80 | 0.23 | 0.06 | −0.08 | 0.71 |
| | (3.18) | (−8.49) | (0.91) | (0.67) | (−2.20) | (0.61) |
| High | 1.77 | −3.49 | 0.28 | 0.18 | −0.20 | 6.52 |
| | (2.40) | (−5.40) | (0.75) | (1.70) | (−2.31) | (3.76) |
| High−Low | 0.19 | 1.31 | 0.05 | 0.12 | −0.12 | 5.82 |
| | (0.32) | (1.98) | (0.21) | (1.25) | (−1.45) | (3.56) |

Table 2.A10: Cross-sectional regressions with dummy variables: Illiquidity computed using 12-month data

The table reports the time-series averages of the Fama and MacBeth (1973) cross-sectional regression coefficient estimates. The setup is the same as in Table 2.3 except that a stock's illiquidity (proxied by the average bid-ask spread ($BAS$)) in month $\tau$ is computed using one year's worth of daily data covering the 12-month period including months $\tau-11$ through $\tau$, inclusive, and requires a minimum of 200 valid daily observations. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.3 in the main chapter.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ | $RDME * BAS_H$ | $RDME * BAS_L$ | $BAS_H$ | $BAS_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.17 | −5.67 | 0.28 | 0.32 | −0.07 | 4.16 | | | | |
| (2.27) | (−12.56) | (1.20) | (3.47) | (−1.42) | (5.19) | | | | |
| 1.18 | −5.73 | 0.30 | 0.31 | −0.10 | 4.75 | | −4.97 | | 0.43 |
| (2.40) | (−12.69) | (1.37) | (3.70) | (−2.31) | (5.95) | | (−6.76) | | (2.71) |
| 1.41 | −5.82 | 0.30 | 0.30 | −0.09 | 2.00 | 4.08 | | −0.37 | |
| (3.26) | (−13.20) | (1.40) | (3.62) | (−2.35) | (2.44) | (5.49) | | (−1.80) | |
| 1.38 | −5.86 | 0.31 | 0.29 | −0.11 | 2.88 | 3.20 | −3.08 | −0.31 | 0.32 |
| (3.24) | (−13.23) | (1.54) | (3.71) | (−3.02) | (3.34) | (4.11) | (−4.31) | (−1.65) | (2.40) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.12 | −3.70 | 0.46 | 0.17 | −0.07 | 3.44 | | | | |
| (1.97) | (−6.99) | (1.58) | (1.57) | (−1.58) | (2.25) | | | | |
| 1.16 | −3.74 | 0.45 | 0.15 | −0.09 | 4.39 | | −4.36 | | 0.28 |
| (2.17) | (−7.17) | (1.65) | (1.55) | (−2.17) | (2.69) | | (−3.08) | | (2.17) |
| 1.43 | −3.94 | 0.44 | 0.11 | −0.10 | 1.56 | 5.58 | | −0.52 | |
| (2.83) | (−7.69) | (1.73) | (1.23) | (−2.60) | (1.72) | (3.90) | | (−2.50) | |
| 1.45 | −3.95 | 0.45 | 0.10 | −0.11 | 2.44 | 4.68 | −2.15 | −0.49 | 0.12 |
| (2.91) | (−7.70) | (1.78) | (1.20) | (−2.85) | (1.56) | (3.14) | (−1.61) | (−2.53) | (1.24) |

Table 2.A11: Double sorts on illiquidity and R&D intensity: Illiquidity computed using 12-month data

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and R&D intensity. The setup is the same as in Table 2.4 except that a stock's illiquidity (proxied by the average bid-ask spread) in month $\tau$ is computed using one year's worth of daily data covering the 12-month period including months $\tau-11$ through $\tau$, inclusive, and requires a minimum of 200 valid daily observations. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Low illiquidity | | | | High illiquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.76 | 0.67 | 0.86 | 0.10 | −0.34 | 0.50 | 0.59 | 0.93 |
| | (4.61) | (3.58) | (3.69) | (0.56) | (−0.62) | (0.99) | (1.13) | (2.73) |
| FF3 $\alpha$ | 0.24 | 0.12 | 0.43 | 0.18 | −1.67 | −0.59 | −0.38 | 1.29 |
| | (2.99) | (1.79) | (3.58) | (1.16) | (−5.50) | (−2.28) | (−1.49) | (3.84) |
| FFC $\alpha$ | 0.24 | 0.15 | 0.38 | 0.14 | −0.96 | 0.02 | 0.04 | 1.00 |
| | (2.78) | (2.31) | (3.05) | (0.84) | (−2.91) | (0.07) | (0.16) | (2.79) |
| FF5 $\alpha$ | 0.13 | 0.00 | 0.27 | 0.14 | −1.08 | 0.14 | 0.34 | 1.42 |
| | (1.50) | (0.07) | (1.74) | (0.70) | (−3.63) | (0.58) | (1.37) | (3.98) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 1.00 | 0.92 | 1.13 | 0.12 | 1.23 | 1.30 | 1.76 | 0.53 |
| | (5.08) | (4.45) | (4.58) | (0.73) | (3.43) | (3.34) | (4.11) | (1.88) |
| FF3 $\alpha$ | 0.37 | 0.22 | 0.55 | 0.19 | 0.08 | 0.31 | 0.89 | 0.81 |
| | (3.19) | (2.54) | (4.17) | (1.16) | (0.49) | (1.84) | (4.44) | (3.03) |
| FFC $\alpha$ | 0.35 | 0.24 | 0.49 | 0.14 | 0.35 | 0.60 | 1.08 | 0.73 |
| | (3.16) | (2.88) | (3.72) | (0.98) | (2.19) | (3.54) | (5.60) | (2.88) |
| FF5 $\alpha$ | 0.11 | 0.01 | 0.38 | 0.26 | 0.28 | 0.84 | 1.38 | 1.09 |
| | (1.14) | (0.18) | (2.97) | (1.55) | (1.54) | (5.66) | (7.70) | (4.19) |

Table 2.A12: Cross-sectional regressions: Illiquidity computed using 12-month data and updated yearly

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. At the end of June of each year $t$, stocks are sorted into three groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of illiquidity measured by the average bid-ask spread ($BAS$). Then, in each month from July of year $t$ to June of year $t+1$ for the Low (High) illiquidity group, I run a cross-sectional regression of monthly return on prior one-month return ($R_{1,1}$), prior year's return skipping the last month ($R_{12,2}$, i.e., return from month $\tau-12$ to month $\tau-2$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), and R&D intensity measured by $RDME$ (i.e., R&D expenditure scaled by $ME$). $BAS$ is computed at the end of June of each year $t$ using one year's worth of daily data covering the 12-month period including July of year $t-1$ through June of year $t$, inclusive, and requires a minimum of 200 valid daily observations. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate and a valid illiquidity estimate in a given year $t$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity groups. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.1 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.75 | −4.44 | 0.59 | 0.10 | −0.04 | 1.04 |
| | (1.67) | (−10.04) | (2.16) | (1.27) | (−1.12) | (1.46) |
| High | 2.29 | −6.90 | −0.07 | 0.35 | −0.38 | 5.16 |
| | (3.93) | (−12.78) | (−0.32) | (4.09) | (−4.72) | (6.45) |
| High−Low | 1.54 | −2.47 | −0.66 | 0.26 | −0.34 | 4.12 |
| | (3.35) | (−4.35) | (−4.11) | (3.20) | (−4.03) | (5.01) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.30 | −5.20 | 0.27 | 0.11 | −0.05 | 1.58 |
| | (2.52) | (−8.87) | (0.88) | (1.25) | (−1.32) | (1.29) |
| High | 1.21 | −2.92 | 0.44 | 0.18 | −0.12 | 5.47 |
| | (1.89) | (−4.78) | (1.45) | (1.68) | (−1.53) | (3.24) |
| High−Low | −0.10 | 2.28 | 0.17 | 0.07 | −0.06 | 3.89 |
| | (−0.18) | (3.55) | (0.84) | (0.70) | (−0.89) | (2.33) |

Table 2.A13: Cross-sectional regressions with dummy variables: Illiquidity computed using 12-month data and updated yearly

The table reports the time-series averages of the Fama and MacBeth (1973) cross-sectional regression coefficient estimates. At the end of June of each year $t$, dummy variables are created by sorting stocks into three groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of illiquidity measured by the average bid-ask spread ($BAS$). Then, in each month from July of year $t$ to June of year $t$+1, I run cross-sectional regressions of monthly return on prior one-month return ($R_{1,1}$), prior year's return skipping the last month ($R_{12,2}$, i.e., return from month $\tau$−12 to month $\tau$−2), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), R&D intensity measured by $RDME$ (i.e., R&D expenditure scaled by $ME$), and illiquidity dummy and interaction variables. $BAS$ is computed at the end of June of each year $t$ using one year's worth of daily data covering the 12-month period including July of year $t$−1 through June of year $t$, inclusive, and requires a minimum of 200 valid daily observations. $BAS_H$ ($BAS_L$) is a dummy variable equal to one for stocks in the High (Low) illiquidity group formed at the end of June of each year $t$ and is zero otherwise. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate and a valid illiquidity estimate in a given year $t$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.1 in the main chapter.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ | $RDME * BAS_H$ | $RDME * BAS_L$ | $BAS_H$ | $BAS_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.19 | −5.64 | 0.27 | 0.32 | −0.07 | 4.17 | | | | |
| (2.32) | (−12.72) | (1.16) | (3.44) | (−1.43) | (5.15) | | | | |
| 1.19 | −5.70 | 0.27 | 0.31 | −0.09 | 4.70 | | −4.70 | | 0.36 |
| (2.41) | (−12.85) | (1.20) | (3.73) | (−2.09) | (5.88) | | (−6.43) | | (2.39) |
| 1.39 | −5.76 | 0.25 | 0.30 | −0.08 | 2.41 | 3.59 | | −0.31 | |
| (3.07) | (−13.28) | (1.12) | (3.52) | (−2.07) | (2.82) | (4.39) | | (−1.59) | |
| 1.36 | −5.80 | 0.26 | 0.29 | −0.09 | 3.24 | 2.77 | −3.20 | −0.25 | 0.25 |
| (3.02) | (−13.33) | (1.17) | (3.68) | (−2.54) | (3.69) | (3.30) | (−4.70) | (−1.44) | (1.99) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.16 | −3.65 | 0.43 | 0.17 | −0.07 | 3.39 | | | | |
| (2.05) | (−7.02) | (1.48) | (1.66) | (−1.62) | (2.20) | | | | |
| 1.19 | −3.70 | 0.42 | 0.16 | −0.09 | 4.17 | | −3.37 | | 0.24 |
| (2.23) | (−7.22) | (1.50) | (1.68) | (−2.13) | (2.51) | | (−2.31) | | (2.02) |
| 1.42 | −3.83 | 0.39 | 0.12 | −0.10 | 2.40 | 2.90 | | −0.38 | |
| (2.73) | (−7.61) | (1.40) | (1.44) | (−2.47) | (1.95) | (2.07) | | (−1.99) | |
| 1.41 | −3.84 | 0.39 | 0.12 | −0.10 | 3.60 | 1.67 | −2.65 | −0.33 | 0.14 |
| (2.76) | (−7.66) | (1.43) | (1.44) | (−2.65) | (2.31) | (1.99) | (−1.92) | (−1.85) | (1.54) |

Table 2.A14: Double sorts on illiquidity and R&D intensity: Illiquidity computed using 12-month data and updated yearly

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and R&D intensity. Illiquidity, measured by the average bid-ask spread ($BAS$), is computed at the end of June of each year $t$ using one year's worth of daily data covering the 12-month period including July of year $t-1$ through June of year $t$, inclusive, and requires a minimum of 200 valid daily observations. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. At the end of June of each year $t$, stocks are sorted into three groups using the breakpoints for the bottom 30% (Low (L)), middle 40% (Medium (M)), and top 30% (High (H)) of the ranked values of $BAS$ computed at the end of June of year $t$ and the stocks are held in the assigned groups for the subsequent 12 months. Independently, at the end of June of each year $t$, stocks are sorted into three groups using the breakpoints for the bottom 30% (L), middle 40% (M), and top 30% (H) of the ranked values of $RDME$ computed at the end of June of year $t$ and the stocks are held in the assigned groups for the subsequent 12 months. Nine portfolios are formed from the intersections of the illiquidity and R&D intensity groups and monthly excess returns are then computed from July of year $t$ to June of year $t+1$. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate and a valid illiquidity estimate in a given year $t$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.1 in the main chapter.

| | Low illiquidity | | | | High illiquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.93 | 1.01 | 1.05 | 0.12 | 1.26 | 1.29 | 2.48 | 1.22 |
| | (3.91) | (4.54) | (3.86) | (1.05) | (2.83) | (2.90) | (4.56) | (4.26) |
| FF3 $\alpha$ | 0.15 | 0.21 | 0.18 | 0.03 | 0.27 | 0.32 | 1.55 | 1.28 |
| | (1.32) | (2.42) | (1.48) | (0.25) | (1.02) | (1.42) | (5.01) | (5.10) |
| FFC $\alpha$ | 0.25 | 0.29 | 0.30 | 0.05 | 0.58 | 0.60 | 1.94 | 1.36 |
| | (2.29) | (3.49) | (2.48) | (0.44) | (1.90) | (2.44) | (5.71) | (5.03) |
| FF5 $\alpha$ | −0.06 | 0.06 | 0.08 | 0.14 | 0.59 | 0.82 | 2.08 | 1.50 |
| | (−0.54) | (0.78) | (0.70) | (1.19) | (1.93) | (3.63) | (6.23) | (5.83) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.81 | 0.85 | 1.01 | 0.20 | 0.42 | 0.81 | 1.07 | 0.65 |
| | (3.97) | (4.37) | (4.44) | (1.97) | (1.05) | (2.04) | (2.53) | (2.79) |
| FF3 $\alpha$ | 0.19 | 0.21 | 0.28 | 0.09 | −0.62 | −0.08 | 0.05 | 0.67 |
| | (1.69) | (2.42) | (2.63) | (1.05) | (−4.00) | (−0.43) | (0.27) | (2.86) |
| FFC $\alpha$ | 0.21 | 0.25 | 0.39 | 0.17 | −0.29 | 0.21 | 0.39 | 0.68 |
| | (1.94) | (3.18) | (3.98) | (1.94) | (−1.95) | (1.20) | (1.96) | (2.78) |
| FF5 $\alpha$ | −0.09 | −0.01 | 0.11 | 0.20 | −0.18 | 0.40 | 0.52 | 0.70 |
| | (−1.03) | (−0.13) | (1.13) | (2.30) | (−1.07) | (2.57) | (2.84) | (3.16) |

Table 2.A15: Cross-sectional regressions: $RDAT$ as a measure of R&D intensity

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that a firm's R&D intensity is measured by $RDAT$ (i.e., R&D expenditure scaled by total assets). In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity (measured by the average bid-ask spread) groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDAT$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.95 | −4.07 | 0.53 | 0.14 | −0.05 | 1.15 |
| | (2.37) | (−8.85) | (2.85) | (2.19) | (−1.49) | (1.17) |
| High | 3.17 | −7.69 | −0.72 | 0.62 | −0.55 | 5.97 |
| | (5.04) | (−13.31) | (−1.98) | (7.01) | (−6.40) | (5.40) |
| High−Low | 2.21 | −3.62 | −1.25 | 0.48 | −0.50 | 4.83 |
| | (4.65) | (−5.60) | (−4.59) | (5.12) | (−5.74) | (4.97) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.68 | −5.67 | 0.19 | 0.05 | −0.09 | 1.21 |
| | (3.42) | (−9.48) | (0.83) | (0.69) | (−2.55) | (0.95) |
| High | 1.48 | −3.27 | 0.11 | 0.39 | −0.11 | 3.25 |
| | (2.12) | (−5.49) | (0.29) | (4.09) | (−1.45) | (2.22) |
| High−Low | −0.20 | 2.40 | −0.08 | 0.34 | −0.01 | 2.03 |
| | (−0.38) | (3.70) | (−0.27) | (3.91) | (−0.17) | (1.67) |

Table 2.A16: Cross-sectional regressions with dummy variables: $RDAT$ as a measure of R&D intensity

The table reports the time-series averages of the Fama and MacBeth (1973) cross-sectional regression coefficient estimates. The setup is the same as in Table 2.3 except that a firm's R&D intensity is measured by $RDAT$ (i.e., R&D expenditure scaled by total assets). In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.3 in the main chapter.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDAT$ | $RDAT * BAS_H$ | $RDAT * BAS_L$ | $BAS_H$ | $BAS_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.57 | −5.76 | 0.13 | 0.52 | −0.08 | 3.87 | | | | |
| (2.95) | (−12.86) | (0.53) | (7.41) | (−1.74) | (4.01) | | | | |
| 1.57 | −5.80 | 0.14 | 0.51 | −0.10 | 4.18 | | −1.52 | | 0.25 |
| (3.00) | (−12.95) | (0.61) | (7.69) | (−2.37) | (4.37) | | (−2.19) | | (1.75) |
| 1.75 | −5.96 | 0.13 | 0.50 | −0.10 | 3.31 | 1.76 | | −0.31 | |
| (3.83) | (−13.59) | (0.60) | (7.55) | (−2.65) | (3.38) | (2.12) | | (−1.57) | |
| 1.72 | −5.96 | 0.15 | 0.49 | −0.11 | 3.68 | 1.37 | −1.12 | −0.27 | 0.19 |
| (3.73) | (−13.54) | (0.68) | (7.70) | (−3.07) | (3.91) | (1.78) | (−1.82) | (−1.50) | (1.66) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.17 | −3.61 | 0.40 | 0.28 | −0.06 | 2.35 | | | | |
| (2.00) | (−7.04) | (1.39) | (3.24) | (−1.32) | (1.81) | | | | |
| 1.21 | −3.65 | 0.41 | 0.27 | −0.07 | 2.28 | | 0.22 | | 0.15 |
| (2.15) | (−7.27) | (1.49) | (3.30) | (−1.81) | (1.74) | | (0.20) | | (1.19) |
| 1.40 | −3.79 | 0.44 | 0.23 | −0.09 | 2.83 | −0.03 | | −0.40 | |
| (2.75) | (−7.61) | (1.75) | (2.93) | (−2.37) | (2.21) | (−0.03) | | (−1.93) | |
| 1.43 | −3.81 | 0.44 | 0.23 | −0.10 | 2.69 | 0.11 | −0.38 | −0.39 | 0.06 |
| (2.82) | (−7.68) | (1.79) | (2.98) | (−2.58) | (1.98) | (0.09) | (−0.32) | (−2.09) | (0.63) |

Table 2.A17: Double sorts on illiquidity and R&D intensity: *RDAT* as a measure of R&D intensity

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and R&D intensity. The setup is the same as in Table 2.4 except that a firm's R&D intensity is measured by *RDAT* (i.e., R&D expenditure scaled by total assets). The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Low illiquidity | | | | High illiquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | $RDAT_L$ | $RDAT_M$ | $RDAT_H$ | H−L | $RDAT_L$ | $RDAT_M$ | $RDAT_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.65 | 0.68 | 0.80 | 0.14 | 0.02 | 0.38 | 1.47 | 1.45 |
| | (3.52) | (3.71) | (3.27) | (0.89) | (0.04) | (0.78) | (2.50) | (4.29) |
| FF3 $\alpha$ | 0.19 | 0.17 | 0.06 | −0.13 | −1.20 | −0.71 | 0.26 | 1.46 |
| | (2.36) | (2.83) | (0.41) | (−0.83) | (−3.69) | (−2.99) | (0.86) | (4.48) |
| FFC $\alpha$ | 0.14 | 0.23 | 0.16 | 0.02 | −0.59 | −0.23 | 0.76 | 1.35 |
| | (1.87) | (3.68) | (1.16) | (0.14) | (−1.58) | (−0.93) | (2.37) | (4.26) |
| FF5 $\alpha$ | 0.04 | 0.07 | 0.01 | −0.04 | −0.40 | 0.03 | 0.95 | 1.35 |
| | (0.58) | (1.21) | (0.06) | (−0.22) | (−1.26) | (0.16) | (3.72) | (3.91) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.88 | 0.94 | 1.11 | 0.23 | 1.09 | 1.49 | 2.18 | 1.08 |
| | (4.47) | (4.81) | (4.98) | (2.03) | (2.67) | (3.68) | (4.93) | (3.87) |
| FF3 $\alpha$ | 0.26 | 0.27 | 0.36 | 0.11 | 0.04 | 0.53 | 1.09 | 1.06 |
| | (2.23) | (3.25) | (3.51) | (1.04) | (0.23) | (2.94) | (4.64) | (3.83) |
| FFC $\alpha$ | 0.26 | 0.29 | 0.42 | 0.16 | 0.28 | 0.77 | 1.27 | 0.99 |
| | (2.32) | (3.65) | (4.35) | (1.58) | (1.78) | (4.36) | (5.82) | (3.86) |
| FF5 $\alpha$ | −0.02 | 0.05 | 0.20 | 0.23 | 0.49 | 1.02 | 1.52 | 1.04 |
| | (−0.25) | (0.67) | (2.21) | (2.25) | (3.32) | (6.63) | (7.21) | (3.97) |

Table 2.A18: Cross-sectional regressions: Amihud illiquidity

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. The setup is the same as in Table 2.2 except that the Amihud (2002) illiquidity measure is used for sorting stocks. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low illiquidity groups. All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.2 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.75 | −2.07 | 0.45 | 0.20 | −0.01 | 1.84 |
| | (1.26) | (−3.58) | (1.91) | (1.90) | (−0.22) | (1.37) |
| High | 2.39 | −9.05 | 0.18 | 0.35 | −0.48 | 4.62 |
| | (3.63) | (−13.36) | (0.58) | (2.97) | (−4.95) | (5.34) |
| High−Low | 1.64 | −6.98 | −0.27 | 0.14 | −0.47 | 2.78 |
| | (2.86) | (−9.54) | (−1.17) | (1.33) | (−4.76) | (2.63) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 0.80 | −1.28 | 0.54 | 0.11 | −0.04 | 2.42 |
| | (1.17) | (−1.84) | (2.13) | (1.02) | (−0.71) | (1.61) |
| High | 2.48 | −5.28 | −0.11 | 0.21 | −0.25 | 5.13 |
| | (2.88) | (−7.86) | (−0.22) | (1.74) | (−2.10) | (2.85) |
| High−Low | 1.68 | −4.01 | −0.65 | 0.10 | −0.21 | 2.72 |
| | (2.27) | (−5.62) | (−1.72) | (0.94) | (−1.82) | (1.98) |

Table 2.A19: Cross-sectional regressions with dummy variables: Amihud illiquidity

The table reports the time-series averages of the Fama and MacBeth (1973) cross-sectional regression coefficient estimates. The setup is the same as in Table 2.3 except that the Amihud (2002) illiquidity measure ($ILLIQ$) is used to create dummy variables by sorting stocks into the Low, Medium, and High illiquidity groups. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates are used to compute the breakpoints for illiquidity. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.3 in the main chapter.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ | $RDME * ILLIQ_H$ | $RDME * ILLIQ_L$ | $ILLIQ_H$ | $ILLIQ_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 0.81 | −5.62 | 0.50 | 0.33 | −0.04 | 3.96 | | | | |
| (1.49) | (−11.34) | (2.06) | (3.31) | (−0.76) | (4.58) | | | | |
| 0.92 | −5.62 | 0.49 | 0.33 | −0.07 | 4.38 | | −2.78 | | 0.32 |
| (1.66) | (−11.28) | (2.04) | (3.37) | (−1.35) | (5.17) | | (−2.72) | | (3.01) |
| 1.02 | −5.60 | 0.50 | 0.33 | −0.06 | 2.76 | 2.23 | | −0.24 | |
| (1.83) | (−11.18) | (2.02) | (3.31) | (−1.17) | (2.63) | (2.84) | | (−2.31) | |
| 1.17 | −5.61 | 0.48 | 0.33 | −0.10 | 3.44 | 1.49 | −1.95 | −0.24 | 0.32 |
| (2.08) | (−11.15) | (1.99) | (3.34) | (−1.93) | (3.28) | (1.97) | (−2.00) | (−2.21) | (3.23) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 2.62 | −4.05 | 0.31 | 0.10 | −0.24 | 3.90 | | | | |
| (4.93) | (−7.75) | (1.37) | (1.02) | (−5.58) | (2.62) | | | | |
| 3.14 | −4.09 | 0.28 | 0.10 | −0.32 | 4.21 | | −1.83 | | 0.37 |
| (5.96) | (−7.84) | (1.28) | (1.02) | (−7.09) | (2.77) | | (−1.70) | | (4.06) |
| 1.74 | −3.99 | 0.38 | 0.10 | −0.14 | 2.71 | 3.67 | | 0.37 | |
| (3.14) | (−7.70) | (1.71) | (0.99) | (−3.05) | (1.76) | (3.14) | | (4.24) | |
| 2.22 | −4.02 | 0.36 | 0.10 | −0.22 | 2.61 | 3.65 | −0.08 | 0.36 | 0.29 |
| (3.97) | (−7.77) | (1.66) | (0.96) | (−4.31) | (1.59) | (2.94) | (−0.07) | (4.26) | (3.17) |

Table 2.A20: Double sorts on Amihud illiquidity and R&D intensity

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and R&D intensity. The setup is the same as in Table 2.4 except that the Amihud (2002) illiquidity measure is used for sorting stocks into the Low, Medium, and High illiquidity groups. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Low illiquidity | | | | High illiquidity | | | |
|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.81 | 0.85 | 1.12 | 0.32 | 1.26 | 1.27 | 2.00 | 0.74 |
| | (3.34) | (3.43) | (3.33) | (1.43) | (3.09) | (3.45) | (4.19) | (2.85) |
| FF3 $\alpha$ | −0.03 | 0.04 | 0.16 | 0.19 | 0.30 | 0.36 | 1.05 | 0.74 |
| | (−0.26) | (0.46) | (0.95) | (0.90) | (1.34) | (2.13) | (4.10) | (3.12) |
| FFC $\alpha$ | 0.04 | 0.16 | 0.30 | 0.26 | 0.57 | 0.59 | 1.39 | 0.82 |
| | (0.38) | (2.06) | (1.92) | (1.30) | (2.25) | (3.08) | (5.18) | (3.30) |
| FF5 $\alpha$ | −0.18 | 0.08 | 0.38 | 0.55 | 0.34 | 0.53 | 1.34 | 1.01 |
| | (−1.69) | (0.95) | (2.46) | (2.78) | (1.37) | (2.65) | (4.91) | (4.56) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.64 | 0.69 | 1.04 | 0.40 | 1.64 | 1.64 | 2.43 | 0.79 |
| | (2.66) | (3.05) | (3.92) | (2.38) | (5.98) | (6.00) | (7.03) | (3.49) |
| FF3 $\alpha$ | −0.04 | 0.11 | 0.27 | 0.31 | 0.71 | 0.74 | 1.47 | 0.76 |
| | (−0.40) | (1.39) | (2.39) | (1.93) | (5.63) | (7.77) | (7.84) | (3.49) |
| FFC $\alpha$ | −0.02 | 0.18 | 0.37 | 0.40 | 0.87 | 0.92 | 1.58 | 0.71 |
| | (−0.23) | (2.36) | (3.42) | (2.45) | (6.58) | (9.50) | (9.13) | (3.54) |
| FF5 $\alpha$ | −0.03 | 0.18 | 0.37 | 0.41 | 0.58 | 0.85 | 1.61 | 1.03 |
| | (−0.31) | (2.41) | (3.54) | (2.61) | (4.60) | (7.75) | (9.73) | (5.02) |

Table 2.A21: Double sorts on illiquidity and R&D intensity: 4×4 sort

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and R&D intensity. Illiquidity is measured by the average bid-ask spread ($BAS$). R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. At the end of each month $\tau$, stocks are sorted into four groups using the breakpoints set to the 25th, 50th, and 75th percentiles of the ranked values of $BAS$ in month $\tau$. Independently, at the end of June of each year $t$, stocks are sorted into four groups using the breakpoints set to the 25th, 50th, and 75th percentiles of the ranked values of $RDME$ computed at the end of June of year $t$ and the stocks are held in the assigned groups for the subsequent 12 months. Portfolios are formed every month from the intersections of the illiquidity and R&D intensity groups. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates to compute the breakpoints for illiquidity and R&D intensity separately. Panel A (Panel B) reports the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Low illiquidity | | | | | High illiquidity | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_2$ | $RDME_3$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_2$ | $RDME_3$ | $RDME_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | |
| Excess return | 0.74 | 0.66 | 0.72 | 0.68 | −0.05 | −0.18 | 0.49 | 0.61 | 1.39 | 1.57 |
| | (3.80) | (3.74) | (3.68) | (2.56) | (−0.27) | (−0.30) | (0.92) | (1.15) | (2.59) | (3.59) |
| FF3 $\alpha$ | 0.23 | 0.18 | 0.17 | −0.06 | −0.29 | −1.42 | −0.65 | −0.50 | 0.24 | 1.66 |
| | (2.24) | (2.36) | (1.63) | (−0.33) | (−1.51) | (−4.63) | (−2.11) | (−1.76) | (0.82) | (4.03) |
| FFC $\alpha$ | 0.18 | 0.16 | 0.25 | 0.02 | −0.15 | −0.62 | −0.07 | 0.13 | 0.87 | 1.49 |
| | (1.68) | (2.07) | (2.41) | (0.12) | (−0.81) | (−1.54) | (−0.23) | (0.40) | (2.49) | (2.73) |
| FF5 $\alpha$ | 0.03 | 0.03 | 0.02 | −0.12 | −0.15 | −0.59 | 0.22 | 0.26 | 1.06 | 1.64 |
| | (0.27) | (0.30) | (0.18) | (−0.67) | (−0.75) | (−2.02) | (0.65) | (0.85) | (3.15) | (3.96) |
| Panel B: All-but-microcaps sample | | | | | | | | | | |
| Excess return | 0.61 | 0.67 | 0.70 | 0.74 | 0.13 | 0.18 | 0.69 | 1.04 | 1.39 | 1.21 |
| | (3.40) | (3.67) | (3.49) | (3.50) | (0.82) | (0.41) | (1.54) | (2.36) | (3.25) | (3.41) |
| FF3 $\alpha$ | 0.17 | 0.20 | 0.16 | 0.16 | −0.01 | −0.82 | −0.14 | 0.10 | 0.40 | 1.23 |
| | (1.54) | (1.88) | (1.57) | (1.13) | (−0.08) | (−3.57) | (−0.44) | (0.39) | (1.59) | (3.54) |
| FFC $\alpha$ | 0.08 | 0.17 | 0.18 | 0.19 | 0.11 | −0.40 | 0.11 | 0.51 | 0.82 | 1.22 |
| | (0.69) | (1.53) | (1.61) | (1.32) | (0.68) | (−1.65) | (0.33) | (2.05) | (3.13) | (3.42) |
| FF5 $\alpha$ | −0.02 | 0.02 | −0.07 | 0.01 | 0.02 | −0.32 | 0.47 | 0.64 | 0.90 | 1.22 |
| | (−0.15) | (0.15) | (−0.63) | (0.05) | (0.13) | (−1.50) | (1.65) | (2.49) | (3.53) | (3.91) |

Table 2.A22: Double sorts on illiquidity and R&D intensity: 5×5 sort

The table reports the value-weighted average monthly excess returns (in %) and abnormal returns for portfolios sorted on illiquidity and R&D intensity. Illiquidity is measured by the average bid-ask spread ($BAS$). R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. At the end of each month $\tau$, stocks are sorted into five groups using the breakpoints set to the 20th, 40th, 60th, and 80th percentiles of the ranked values of $BAS$ in month $\tau$. Independently, at the end of June of each year $t$, stocks are sorted into five groups using the breakpoints set to the 20th, 40th, 60th, and 80th percentiles of the ranked values of $RDME$ computed at the end of June of year $t$ and the stocks are held in the assigned groups for the subsequent 12 months. A set of 25 portfolios are formed every month from the intersections of the illiquidity and R&D intensity groups. The sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Low illiquidity | | | | | | High illiquidity | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $RDME_L$ | $RDME_2$ | $RDME_3$ | $RDME_4$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_2$ | $RDME_3$ | $RDME_4$ | $RDME_H$ | H−L |
| Excess return | 0.74 | 0.59 | 0.75 | 0.80 | 0.68 | −0.06 | −0.40 | 0.27 | 0.60 | 0.83 | 1.82 | 2.22 |
| | (3.55) | (3.31) | (3.93) | (3.97) | (2.33) | (−0.27) | (−0.63) | (0.47) | (1.08) | (1.41) | (3.01) | (3.99) |
| FF3 $\alpha$ | 0.22 | 0.13 | 0.21 | 0.20 | −0.01 | −0.23 | −1.79 | −0.79 | −0.55 | −0.35 | 0.61 | 2.40 |
| | (1.73) | (1.22) | (2.27) | (1.56) | (−0.06) | (−0.99) | (−4.67) | (−2.12) | (−1.70) | (−1.17) | (1.72) | (4.59) |
| FFC $\alpha$ | 0.14 | 0.10 | 0.26 | 0.23 | 0.02 | −0.12 | −0.88 | −0.16 | 0.19 | 0.40 | 1.29 | 2.17 |
| | (1.11) | (0.86) | (2.47) | (1.80) | (0.10) | (−0.50) | (−1.84) | (−0.39) | (0.53) | (1.15) | (3.15) | (3.54) |
| FF5 $\alpha$ | 0.00 | 0.00 | −0.02 | −0.01 | −0.04 | −0.04 | −0.99 | 0.17 | 0.42 | 0.51 | 1.48 | 2.48 |
| | (−0.03) | (0.03) | (−0.17) | (−0.07) | (−0.18) | (−0.14) | (−2.71) | (0.45) | (1.06) | (1.65) | (3.68) | (5.12) |

Table 2.A23: Double sorts on illiquidity and R&D intensity after controlling for financial constraints (Hadlock and Pierce, 2010)

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity for both financially constrained and financially unconstrained subsamples. Financial constraint is measured by the SA index developed in Hadlock and Pierce (2010). Illiquidity is measured by the average bid-ask spread. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates for portfolio analysis. At the end of June of each year $t$, I first assign stocks in the full sample to the financially constrained (unconstrained) subsample based on the median value of the distribution of the SA index (i.e., financially constrained (unconstrained) subsample includes stocks above (below) the median). Then for each subsample, I conduct independent double sorts on illiquidity and R&D intensity as in Table 2.4. A similar procedure is followed for stocks in the all-but-microcaps sample. I report the value-weighted (equal-weighted) average monthly excess returns (in %) for portfolios based on the full sample (all-but-microcaps sample). The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Tables 2.1 and 2.4 in the main chapter.

| | Full sample | | | | | | | | All-but-microcaps sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low illiquidity | | | | High illiquidity | | | | Low illiquidity | | | | High illiquidity | | | |
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Financially constrained subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.99 | 1.08 | 1.09 | 0.11 | 0.03 | 0.62 | 1.78 | 1.75 | 0.82 | 1.04 | 1.01 | 0.19 | −0.44 | 0.67 | 0.66 | 1.10 |
| | (3.56) | (3.73) | (3.19) | (0.47) | (0.05) | (1.05) | (3.05) | (4.67) | (3.08) | (3.47) | (3.23) | (0.84) | (−0.91) | (1.39) | (1.30) | (3.17) |
| FF3 $\alpha$ | 0.34 | 0.38 | 0.16 | −0.18 | −1.20 | −0.50 | 0.63 | 1.83 | 0.11 | 0.29 | 0.22 | 0.10 | −1.50 | −0.29 | −0.35 | 1.14 |
| | (2.17) | (2.45) | (0.74) | (−0.75) | (−3.39) | (−1.56) | (1.89) | (4.80) | (0.64) | (1.78) | (1.22) | (0.46) | (−5.92) | (−1.16) | (−1.35) | (3.37) |
| FFC $\alpha$ | 0.35 | 0.36 | 0.28 | −0.07 | −0.34 | 0.17 | 1.26 | 1.60 | 0.10 | 0.32 | 0.26 | 0.16 | −1.17 | 0.20 | 0.27 | 1.45 |
| | (2.11) | (2.24) | (1.29) | (−0.30) | (−0.80) | (0.49) | (3.52) | (3.80) | (0.55) | (2.07) | (1.41) | (0.70) | (−4.70) | (0.72) | (0.94) | (3.88) |
| FF5 $\alpha$ | 0.19 | 0.21 | 0.02 | −0.17 | −0.17 | 0.50 | 1.43 | 1.61 | −0.20 | 0.08 | −0.01 | 0.19 | −0.90 | 0.44 | 0.32 | 1.22 |
| | (1.18) | (1.17) | (0.08) | (−0.72) | (−0.51) | (1.55) | (4.25) | (4.49) | (−1.28) | (0.55) | (−0.06) | (0.83) | (−3.83) | (1.59) | (1.11) | (3.70) |
| Panel B: Financially unconstrained subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.68 | 0.57 | 0.91 | 0.23 | 0.38 | 0.81 | 1.27 | 0.89 | 0.83 | 0.80 | 0.98 | 0.14 | 0.69 | 0.69 | 1.35 | 0.66 |
| | (4.35) | (3.04) | (4.20) | (1.39) | (0.90) | (2.12) | (2.88) | (2.68) | (4.36) | (4.27) | (4.35) | (1.41) | (2.01) | (2.06) | (3.42) | (2.74) |
| FF3 $\alpha$ | 0.25 | 0.07 | 0.31 | 0.06 | −0.74 | −0.18 | 0.14 | 0.88 | 0.25 | 0.17 | 0.24 | −0.01 | −0.41 | −0.26 | 0.24 | 0.66 |
| | (2.54) | (0.80) | (2.16) | (0.38) | (−3.34) | (−0.81) | (0.53) | (2.62) | (2.13) | (1.93) | (2.13) | (−0.08) | (−2.64) | (−1.75) | (1.35) | (2.77) |
| FFC $\alpha$ | 0.17 | 0.07 | 0.31 | 0.14 | −0.23 | 0.11 | 0.58 | 0.81 | 0.24 | 0.17 | 0.28 | 0.03 | −0.04 | 0.01 | 0.59 | 0.63 |
| | (1.71) | (0.78) | (2.01) | (0.81) | (−0.83) | (0.48) | (2.14) | (2.05) | (2.06) | (2.04) | (2.38) | (0.36) | (−0.23) | (0.07) | (3.25) | (2.69) |
| FF5 $\alpha$ | 0.08 | −0.17 | 0.18 | 0.10 | −0.53 | 0.20 | 0.52 | 1.05 | −0.01 | −0.07 | 0.05 | 0.06 | −0.31 | 0.04 | 0.59 | 0.91 |
| | (0.76) | (−2.07) | (1.28) | (0.56) | (−2.23) | (0.87) | (1.82) | (3.15) | (−0.13) | (−0.88) | (0.52) | (0.67) | (−1.39) | (0.28) | (3.32) | (3.77) |

Table 2.A24: Cross-sectional regressions after controlling for volatility

The table reports the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions. At the end of each month $\tau$, I run a cross-sectional regression of illiquidity on a constant and volatility, and collect the residuals. Then, in each month stocks are sorted into three groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of (orthogonalized) illiquidity (i.e., cross-sectional residual). Finally, in each month from July of year $t$ to June of year $t+1$ for the Low (High) orthogonalized illiquidity group formed in the previous month, I run a cross-sectional regression of monthly return on prior one-month return ($R_{1,1}$), prior year's return skipping the last month ($R_{12,2}$, i.e., return from month $\tau-12$ to month $\tau-2$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), and research and development (R&D) intensity measured by $RDME$ (i.e., R&D expenditure scaled by $ME$). Illiquidity is measured by the average bid-ask spread in month $\tau$. Stock return volatility in month $\tau$ is computed as the standard deviation of daily returns over the month $\tau$ and requires a minimum of 15 valid daily observations. In Panel A, the full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid (orthogonalized) illiquidity estimate in a given month $\tau$ are available. In Panel B, the all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks with both nonmissing R&D intensity and valid (orthogonalized) illiquidity estimates are used to compute the breakpoints for (orthogonalized) illiquidity. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low (orthogonalized) illiquidity groups. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables are winsorized at the 1% and 99% levels on a monthly basis prior to running the regressions. The sample period is from January 1975 to December 2016. See also notes to Table 2.1 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $RDME$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.87 | −4.81 | 0.60 | 0.34 | −0.06 | 3.11 |
| | (1.88) | (−8.66) | (3.22) | (3.70) | (−1.51) | (3.58) |
| High | 1.85 | −7.54 | −0.30 | 0.33 | −0.22 | 4.95 |
| | (3.16) | (−13.01) | (−0.93) | (3.27) | (−3.09) | (5.38) |
| High−Low | 0.99 | −2.73 | −0.89 | 0.00 | −0.16 | 1.84 |
| | (2.73) | (−5.36) | (−4.05) | (−0.05) | (−2.34) | (2.66) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.45 | −2.48 | 0.20 | 0.18 | −0.08 | 2.03 |
| | (2.72) | (−4.62) | (0.79) | (1.77) | (−1.96) | (1.43) |
| High | 2.54 | −4.85 | 0.13 | 0.18 | −0.23 | 4.43 |
| | (3.78) | (−7.20) | (0.37) | (1.45) | (−3.72) | (2.80) |
| High−Low | 1.09 | −2.37 | −0.06 | 0.00 | −0.15 | 2.41 |
| | (2.53) | (−3.94) | (−0.29) | (0.00) | (−3.02) | (1.98) |

## Table 2.A25: Double sorts on illiquidity and R&D intensity after controlling for volatility

The table reports the monthly excess returns and abnormal returns for portfolios sorted on illiquidity and research and development (R&D) intensity for both low volatility and high volatility subsamples. Stock return volatility in month $\tau$ is computed as the standard deviation of daily returns over the month $\tau$ and requires a minimum of 15 valid daily observations. Illiquidity is measured by the average bid-ask spread. R&D intensity is measured by $RDME$, which is R&D expenditure scaled by market value of equity. The full sample includes all NYSE-, AMEX-, and NASDAQ-listed nonfinancial ordinary common stocks for which both a valid (i.e., nonmissing) R&D intensity estimate in a given year $t$ and a valid illiquidity estimate in a given month $\tau$ are available. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and I use the remaining stocks with both nonmissing R&D intensity and valid illiquidity estimates for portfolio analysis. At the end of each month $\tau$, I first assign stocks in the full sample to the low (high) volatility subsample based on the median value of the distribution of the return volatility (i.e., low (high) volatility subsample includes stocks below (above) the median). Then for each subsample, I conduct independent double sorts on illiquidity and R&D intensity as in Table 2.4. A similar procedure is followed for stocks in the all-but-microcaps sample. I report the value-weighted (equal-weighted) average monthly excess returns (in %) for portfolios based on the full sample (all-but-microcaps sample). The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L denotes the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1975 to December 2016. See also notes to Table 2.A1 and Table 2.4 in the main chapter.

| | Full sample | | | | | | | | All-but-microcaps sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low illiquidity | | | | High illiquidity | | | | Low illiquidity | | | | High illiquidity | | | |
| | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L | $RDME_L$ | $RDME_M$ | $RDME_H$ | H−L |
| Panel A: Low volatility subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.64 | 0.45 | 0.76 | 0.12 | 0.66 | 0.80 | 1.26 | 0.60 | 0.81 | 0.78 | 0.86 | 0.06 | 0.91 | 0.87 | 1.17 | 0.26 |
| | (3.65) | (2.47) | (3.67) | (0.81) | (2.07) | (2.66) | (3.58) | (2.23) | (4.15) | (3.99) | (4.06) | (0.48) | (3.51) | (3.57) | (4.47) | (1.74) |
| FF3 $\alpha$ | 0.17 | −0.03 | 0.17 | 0.00 | −0.10 | 0.18 | 0.38 | 0.49 | 0.24 | 0.13 | 0.19 | −0.05 | 0.03 | 0.11 | 0.27 | 0.24 |
| | (1.58) | (−0.34) | (1.18) | (−0.02) | (−0.60) | (1.07) | (1.77) | (1.72) | (1.99) | (1.17) | (1.43) | (−0.43) | (0.25) | (1.06) | (2.47) | (1.58) |
| FFC $\alpha$ | 0.09 | −0.04 | 0.20 | 0.11 | 0.12 | 0.41 | 0.71 | 0.59 | 0.23 | 0.10 | 0.21 | −0.02 | 0.11 | 0.24 | 0.45 | 0.34 |
| | (0.82) | (−0.37) | (1.33) | (0.66) | (0.63) | (2.26) | (3.18) | (2.11) | (1.89) | (0.93) | (1.54) | (−0.18) | (0.86) | (2.25) | (3.59) | (2.07) |
| FF5 $\alpha$ | −0.04 | −0.24 | 0.07 | 0.11 | 0.00 | 0.48 | 0.60 | 0.60 | 0.00 | −0.10 | 0.00 | 0.00 | −0.14 | 0.09 | 0.31 | 0.45 |
| | (−0.34) | (−2.43) | (0.51) | (0.64) | (−0.02) | (2.77) | (2.67) | (2.22) | (−0.00) | (−1.02) | (0.01) | (0.02) | (−1.06) | (0.88) | (2.44) | (2.87) |
| Panel B: High volatility subsample | | | | | | | | | | | | | | | | |
| Excess return | 0.62 | 0.90 | 1.11 | 0.49 | −0.25 | 0.21 | 1.61 | 1.86 | 0.85 | 1.01 | 1.55 | 0.70 | 0.99 | 1.41 | 2.16 | 1.17 |
| | (1.80) | (2.74) | (2.76) | (1.47) | (−0.40) | (0.37) | (2.55) | (4.18) | (3.27) | (3.87) | (4.73) | (3.06) | (2.15) | (3.25) | (4.49) | (3.61) |
| FF3 $\alpha$ | −0.13 | 0.09 | 0.16 | 0.29 | −1.73 | −1.00 | 0.31 | 2.04 | 0.01 | 0.25 | 0.74 | 0.73 | −0.15 | 0.42 | 1.06 | 1.21 |
| | (−0.60) | (0.54) | (0.68) | (0.88) | (−4.76) | (−3.21) | (0.80) | (4.37) | (0.07) | (2.59) | (3.35) | (2.90) | (−0.72) | (2.00) | (3.78) | (3.79) |
| FFC $\alpha$ | 0.05 | 0.39 | 0.43 | 0.37 | −0.78 | −0.19 | 0.98 | 1.76 | 0.07 | 0.34 | 0.79 | 0.72 | 0.22 | 0.74 | 1.30 | 1.08 |
| | (0.26) | (2.30) | (1.74) | (1.15) | (−1.67) | (−0.51) | (2.23) | (3.23) | (0.64) | (3.42) | (3.59) | (2.97) | (0.91) | (3.47) | (4.87) | (3.44) |
| FF5 $\alpha$ | −0.05 | 0.35 | 0.30 | 0.35 | −0.76 | −0.14 | 1.19 | 1.95 | −0.14 | 0.26 | 0.79 | 0.93 | 0.43 | 0.97 | 1.63 | 1.20 |
| | (−0.21) | (2.10) | (1.25) | (1.04) | (−2.11) | (−0.36) | (2.81) | (4.16) | (−1.34) | (2.90) | (3.62) | (3.88) | (2.23) | (5.00) | (6.15) | (3.92) |

# Chapter 3

# Product market competition, labor mobility, and asset prices in the cross-section

## 3.1 Introduction

Firms in industries employing workers whose labor skills are portable to other industries are more exposed to systematic risk than those in industries where workers have less portable skills (Donangelo, 2014). Since product market competition ($PMC$) is identified as a source of increased return to skilled or industry-specific workforce and cost of employers, I conjecture $PMC$ sharpens the risk profile of firms in competitive industries than those in less competitive industries, if the firms have the same level of labor mobility ($LM$). Therefore, this chapter mainly studies the effect of $PMC$ on the positive relation between $LM$ and stock returns. The testable hypothesis is that the positive $LM$-return relation is stronger among stocks in competitive industries. Namely, a higher market competition enhances or drives the relation between $LM$ and stock returns.

The hypothesis is tested by using both double-sorting portfolio analysis and Fama and MacBeth (1973) cross-sectional regressions. I find that the positive $LM$-return relation is potentially driven by $PMC$, in other words, a higher $PMC$ strengthens the positive relation. In my empirical analysis, I employ $LM$ estimate of Donangelo (2014) based on the level of interindustry dispersion of workers across occupations. For $PMC$ proxy, I use the Herfindahl-Hirschman Index (HHI) of Hou and Robinson (2006), which is commonly used in the literature on market competition (see, e.g., Hou and Robinson, 2006; Giroud and Mueller, 2011; Valta, 2012; Gu, 2016).[1]

[1] To improve the accuracy of the estimate, I also follow Hou, Xue, and Zhang (2017b) to adjust the estimation which is reported in the main body. On the other hand, the results of original estimate of HHI are reported in Appendix, which both estimates show quantitatively and qualitatively similar results. Additionally, the fitted HHI of Hoberg and Phillips (2010), which capture information of both private and

Firstly, I test my hypothesis by double sorting stocks on the ranked values of $LM$ and $PMC$ proxies. The results of sorted portfolio analysis confirm that the positive $LM$-return relation is stronger among stocks in competitive industries. For instance, the value-weighted excess return of the high-minus-low $LM$ portfolio is 0.83% ($t$-statistic = 3.05) for stocks in High competition group (competitive industries). But the significant high-minus-low portfolio return does not hold for stocks in the Low competition group (concentrated industries), which the portfolio excess return is −0.15% ($t$-statistic = −0.91). The abnormal returns provided by the Ferson and Schadt (1996) conditional-CAPM (FS), the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model document the same pattern. Additionally, I also double sort stocks by using the all-but-microcaps sample and provide equal-weighted portfolio returns, and the findings are consistent with the aforementioned results.[2] For example, the equal-weighted excess return of the high-minus-low $LM$ portfolio is 0.84% ($t$-statistic = 2.60) for stocks in the High competition group and 0.16% ($t$-statistic = 1.31) for stocks in the Low competition group.

In the Fama and MacBeth (1973) regression analysis, the results document that the positive $LM$-return relation only significantly exists among stocks in competitive industries. Firstly, I sort stocks into three groups based on the ranked value of $PMC$ proxy, and then run the Fama-MacBeth regression on $LM$ with four common risk characteristics (short-term reversal, momentum, book-to-market, and size). The results show that the coefficient of $LM$ is significantly higher for stocks in competitive industries. For example, the coefficient of $LM$ for stocks in competitive industries is 0.46 ($t$-statistic = 4.50), and it is 0.08 ($t$-statistic = 1.30) for stocks in concentrated industries, and the difference is 0.38 ($t$-statistic = 3.00), taking the full sample.[3] Secondly, I create interaction terms involving dummy variables, which the dummy variables are created based on the ranked value of $PMC$ proxy and the interaction terms are $LM$ estimate multiplies the dummy variables, and add the interaction terms and dummy variables into Fama-MacBeth regressions. The results show that the positive $LM$-return relation increases with $PMC$. For instance, when analysed

public firms, is also employed for robustness check, and the results still hold.

[2] Dropping microcaps reduces the impact of small stocks and providing the equal-weighted portfolio returns eliminates the domination of big stocks. Therefore, dropping microcaps and providing the equal-weighted portfolio returns help to reveal that $PMC$ independently drives the $LM$-return relation, which is unrelated with size effect.

[3] To minimize the impact of small stocks, I follow previous studies (e.g., Ball, Gerakos, Linnainmaa, and Nikolaev, 2015; Fama and French, 2008; Hou, Xue, and Zhang, 2015) to drop small stocks which are market equity below the 20th NYSE percentile, and construct the all-but-microcaps sample. The result is consistent with using the full sample, which the coefficient of $LM$ for stocks in competitive industries is 0.36 ($t$-statistic = 2.70) and it is 0.06 ($t$-statistic = 1.12) for stocks in concentrated industries, and the difference is 0.30 ($t$-statistic = 2.07).

assigning the dummy variable equals to one if stocks in the lowest $PMC$ group (concentrated industries) and equals to zero otherwise, the coefficient of $LM$ is 0.25 ($t$-statistic = 3.08) which is for all other stocks rather than stocks in concentrated industries, and the coefficient of the interaction term is $-0.18$ ($t$-statistic = $-1.66$), taking the full sample. The results simply indicate that the $LM$ has no significant effect on future stock returns among stocks in concentrated industries, since the summation to the coefficients of $LM$ and the interaction term is 0.07 ($t$-statistic = 1.08). The results are consistent with using the all-but-microcaps sample.

This study contributes to the literature on the implications of labor studies for asset pricing (see, among others, Belo, Li, Lin, and Zhao, 2017; Belo, Lin, and Bazdresch, 2014; Danthine and Donaldson, 2002; Donangelo, 2014; Donangelo, Gourio, Kehrig, and Palacios, 2017; Eiling, 2013; Kuehn, Simutin, and Wang, 2017; Merz and Yashiv, 2007; Santos and Veronesi, 2005). I illustrate a picture of understanding the positive $LM$-return relation from a $PMC$ perspective, which documents a robuster and stronger positive $LM$-return relation among stocks in competitive industries. Additionally, the results also show that $PMC$ potentially and independently drives a stronger $LM$-return relation by controlling the existing documented risk characteristics such as size, value, short-term reversal, and momentum.

The remainder of this chapter is structured as follows. Section 3.2 develops my testable hypothesis linking product market competition and labor mobility to average stock returns. Section 3.3 describes the data and provides summary statistics of variables of interest. Section 3.4 discusses the main empirical results supporting the hypothesis. Finally, Section 3.5 concludes this chapter. A separate Appendix contains additional results and robustness checks.

## 3.2 Hypothesis development

Guadalupe (2007) shows that the increasing product market competition increases the sensitivity of profit to cost, which an increase in competition when firms have different marginal costs always raises the profits of a firm relative to those of a less efficient one. Extensively, if skilled or industry-specific workers are in limited supply and the worker are a quasi-fixed factor characterised by reducing unit costs, then the increased value of a cost reduction implies that employees with higher productivity are more valuable when the product market competition increases. Therefore, if there are two firms with the same level of labor

mobility, the one which operates in higher competitive industry has higher risk by retaining the employees who are more valuable.

Additionally, literature documents that firms in higher competitive industries tend to invest on innovation and cost-reducing technologies (see, among others, Blundell, Griffith, and Van Reenen, 1999; Geroski et al., 1995; Nickell, 1996). Hence, if a firm pursues innovation and growth, it will aggravate the shortage of higher-skilled or industry-specific workers. So the product market competition can be considered as a source of increased return to skill and cost to employers. Consequently, the cost to firms in relative higher competitive industries will be higher than in lower competitive industries, if the firms face the same level of labor mobility or have the same demand of skilled or industry-specific workforce. To compensate investors by holding the stocks with higher labor mobility and in higher competitive industries, the stocks should provide higher returns for bearing higher risk.

**Hypothesis:** The positive relation between labor mobility and future stock returns strengthens with product market competition.

## 3.3 Data and summary statistics

This section describes the data used in the empirical analyses and the construction of product market competition and labor mobility measures, and presents the summary statistics.

### 3.3.1 Data and measures of product market competition and labor mobility

In this chapter, I resort to a variety of data sources to conduct the empirical analyses. Firms' monthly stock returns and accounting information are sourced from the Center for Research in Security Prices (CRSP) and the Compustat Annual Industrial Files, respectively. My preliminary sample includes all NYSE/AMEX/NASDAQ-listed ordinary common stocks (CRSP share code SHRCD = 10 or 11). I filter the preliminary sample by excluding firms whose four-digit primary standard industrial classification (SIC) code is between 4900 and 4999 (regulated firms) or between 6000 and 6999 (financial firms), and firms with a nonpositive book value of equity. To account for delisting bias, I follow the approach of Shumway (1997) by imputing a return of $-30\%$ if the delisting return is missing and the delisting is performance-related; however, this adjustment has no material effect on my empirical findings. The data on delisting returns are sourced from the CRSP. My sample is restricted to the period from January 1990 to December 2016. This is due to the lack of availability of

labor mobility data for a long period in the public domain, described below, which are a key ingredient of my analyses.

I construct two samples from the filtered preliminary sample, namely, the full sample and the all-but-microcaps sample. The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks for which both nonmissing product market competition and labor mobility estimates in a given year are obtainable. Conversely, the all-but-microcaps sample excludes stocks, from the full sample, with an end-June market value of equity below the 20th percentile of the NYSE market capitalization cross-sectional distribution. Excluding microcaps (i.e., very small stocks) helps mitigating their possible undue influence on the empirical results from the full sample. In an average month, there are 2718 firms available in the full sample, whereas 1148 firms in the all-but-microcaps sample. I further employ all accounting variables at the end of June of calendar year $t$ by using accounting information available for the fiscal year ending in the calendar year $t-1$ from Compustat. This adjustment procedure, as suggested in Fama and French (1992), provides time long enough for accounting information to be impounded into firms' stock prices.

To measure product market competition (also known as market concentration) for an industry[4], I use the Herfindahl-Hirschman Index (HHI). Formally, the index is defined as

$$\text{HHI}_{j,t} = \sum_{i=1}^{N_j} s_{i,j,t}^2, \tag{3.1}$$

where $s_{i,j,t}$ is the market share of firm $i$ in industry $j$ in year $t$, $N_j$ is the number of firms operating in industry $j$ in year $t$, and $\text{HHI}_{j,t}$ is the Herfindahl-Hirschman Index of industry $j$ in year $t$. For each industry, I first aggregate the squared market shares of all firms in that industry in a given year $t$ and then average the HHI values over the past three years. This prevents undue influence of potential data errors in the estimation of market concentration. To further improve the accuracy of the product market competition measure, I follow Hou, Xue, and Zhang (2017b) by excluding an industry if the market share data are available for fewer than five firms or 80% of all firms in that industry. Throughout this chapter, I compute the HHI using the market shares based on net sales (Compustat item SALE) and denote the resulting measure of product market competition by $HSALE$.

I also resort to three alternative measures of market competition in order to establish

[4] As in Gu (2016), Hoberg and Phillips (2010), and Hou and Robinson (2006), I use three-digit SIC codes to define industry membership.

the robustness of the empirical findings. The first of them, denoted $HAT$, is the product market competition measured analogous to $HSALE$ but using total assets (Compustat item AT) instead of net sales (Compustat item SALE). The second of them, denoted $HSALE_{HR}$, is measured as per Hou and Robinson (2006), where I abstain from excluding an industry for which the market share data are available for fewer than five firms or 80% of all firms in that industry. The last of them, denoted $HSALE_{HP}$, is obtained from Hoberg and Phillips (2010), which considers both private and public firms operating in a given industry and uses the fitted HHI to capture competitiveness.[5] I multiply the values of $HSALE$, $HAT$, $HSALE_{HR}$, and $HSALE_{HP}$ by minus one to simplify interpretation of the empirical results. As a result, a higher value of these indexes indicates a higher level of market competition. In other words, the product market is shared by many competing firms. All of my product market competition measures are estimated at the end of June of each year $t$.

The measure of labor mobility, denoted $LM$, is based on Donangelo (2014), which captures the level of interindustry dispersion of workers across occupations. Specifically, $LM$ is constructed in two stages. In the first stage, the interindustry concentration of workers assigned to each occupation is estimated. This essentially proxys for (the inverse of) workers' intrinsic flexibility to switch industries. The second stage involves aggregating the occupation-level concentration measure by industry, weighted by the average annual wage expenditure corresponding to each occupation. Further details of estimating $LM$ are provided in Donangelo (2014) and the standardized data are sourced from Andrés Donangelo's website.[6] Consistent with Donangelo (2014), labor mobility, $LM$, is lagged 18 months in all of my empirical analyses.

In the portfolio analyses, I utilize four prominent asset pricing models to compute average abnormal returns. My list of models comprises the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. My motivation for using the FS model is to account for possible time-variation in model betas and risk premiums. The time-series data on pricing factors (i.e., market, size, value, momentum, profitability, and investment) of these models and monthly risk-free security returns are again sourced from the Data Library maintained by Kenneth R. French. To compute monthly average abnormal returns on portfolios relative to the FS model, I obtain data of a set of instruments comprising the dividend yield of

[5] Estimates of $HSALE_{HP}$ are sourced from the Hoberg-Phillips Data Library at http://hobergphillips.usc.edu/industryconcen.htm.

[6] See https://faculty.mccombs.utexas.edu/donangelo/.

the Standard and Poor's 500 Index from Robert Shiller's website[7], and the term spread between 10-year and three-month Treasury constant-maturity yields, the Treasury bill rate, and the default spread between BAA and AAA-rated corporate bond yields from Amit Goyal's website.[8] These instruments are demeaned before computing average abnormal returns on portfolios.

I use several control variables in my cross-sectional regressions. These include firm-level attributes such as past one-month return, past one-year return skipping the last month, book-to-market equity, and size. Following Fama and French (1992, 1993), I compute the book-to-market ratio, denoted $BM$, at the end of June of year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$.[9] In the event of a missing book value of equity, I resort to the Davis, Fama, and French (2000) book value of equity from the Data Library maintained by Kenneth R. French.[10] The market value of equity, denoted $ME$, is computed as absolute price times number of equity shares outstanding at the end of June of each year $t$.

### 3.3.2 Summary statistics

The empirical analyses begin by investigating financial and accounting characteristics across $LM$-sorted portfolios to help understand the data. I allocate stocks in the full sample into three portfolios at the end of June of year $t$ based on the NYSE breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $LM$.[11] The portfolios are rebalanced annually at the end of June of year $t+1$. Panel A of Table 3.1 presents the time-series averages of the cross-sectional mean characteristics including $HSALE$, $ME$, $BM$, past one-month return ($R_{1,1}$), and past one-year return ($R_{12,2}$) skipping the last month. I see that the Low $LM$-sorted portfolio comprises stocks from the least competitive (or, equivalently, the most concentrated) industries, whereas the Medium $LM$-sorted portfolio comprises stocks from the most competitive (or, equivalently, the least concentrated) industries. Consistent with Donangelo (2014), I also find that the High $LM$ portfolio contains stocks smaller than those comprising the other portfolios. The average market capitalization of such stocks amounts to \$2740.02 million. It is worth mentioning

[7] See http://http://www.econ.yale.edu/~shiller/data.htm.
[8] See http://www.hec.unil.ch/agoyal/.
[9] Details of the construction of the book value of equity can be found in Novy-Marx (2013).
[10] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[11] Table 3.A1 in the Appendix provides summary statistics of portfolios based on the all-but-microcaps sample. To conserve space, I abstain from reporting summary statistics of portfolios of stocks sorted separately on $HAT$, $HSALE_{HR}$, and $HSALE_{HP}$; these are available upon request.

that both $HSALE$ and $ME$ exhibit a nearly inverted U-shaped relation with $LM$. On the contrary, average $BM$ ratios show a monotonically decreasing relation with $LM$. That is, stocks in the High $LM$ portfolio tend to be a growth stock, while stocks in the Low $LM$ portfolio tend to be a value stock. Furthermore, past one-month and one-year returns increase monotonically with $LM$.

I then examine whether one-way sorts on product market competition or labor mobility alone generate a pattern in average excess returns over the risk-free rate. Panel B of Table 3.1 reports the results from such exercise where I construct three portfolios based on the NYSE breakpoints set to the bottom 30%, middle 40%, and top 30% of the ranked values of $HSALE$ or $LM$ at the end of June of each year $t$. On the one hand, I find that the value-weighted average monthly excess returns on $HSALE$-sorted portfolios generate neither a monotonically increasing nor a monotonically decreasing pattern. Moreover, the high-minus-low $HSALE$ portfolio (also known as a zero-net investment portfolio) yields a statistically insignificant average return of $-0.11\%$ per month ($t$-statistic $= -0.57$). On the other hand, a monotonically increasing pattern emerges for the equal-weighted average monthly excess returns when moving from the Low $HSALE$ portfolio to the High $HSALE$ portfolio. However, the monthly average return of 0.19% for the high-minus-low portfolio is statistically insignificant at conventional levels ($t$-statistic $= 0.82$). Analyzing the portfolios of stocks sorted on $LM$, I find that the value-weighted (equal-weighted) average monthly excess portfolio returns increase monotonically, from 0.61% (0.73%) for the Low $LM$ portfolio to 0.88% (1.14%) for the High $LM$ portfolio. The value-weighted (equal-weighted) average return of 0.27% (0.41%) per month for the high-minus-low $LM$ is statistically indistinguishable (distinguishable) from zero, with a $t$-statistic of 1.56 (2.33). Although the value-weighted average monthly return on the high-minus-low portfolio is statistically insignificant at conventional levels, the portfolio generates an economically large and statistically significant average return of 0.83% per month ($t$-statistic $= 3.05$) for stocks in competitive industries (see Table 3.2).

Panel C of Table 3.1 presents the results from the univariate portfolio analyses where stocks are sorted into quintile portfolios. By construction, the Low $HSALE$ ($LM$) portfolio contains stocks below the 20th percentile of the NYSE cross-sectional distribution of $HSALE$ ($LM$), while the High $HSALE$ ($LM$) portfolio contains stocks above the 80th percentile of the NYSE cross-sectional distribution of $HSALE$ ($LM$). Once again, the value-weighted average monthly excess returns on $HSALE$-sorted portfolios exhibit no meaningful pattern. But similar to the pattern in Panel B, the equal-weighted average excess returns increase monotonically with market competition. I also find that both the value-weighted and the

equal-weighted average monthly returns on the high-minus-low $HSALE$ portfolio are statistically indistinguishable from zero; they are 0.07% ($t$-statistic = 0.35) and 0.22% ($t$-statistic = 0.83) per month, respectively. Examining the portfolios of firms sorted on $LM$, it can be seen that both the value-weighted and the equal-weighted average excess returns on portfolios generate neither a monotonically increasing nor a monotonically decreasing pattern. The high-minus-low $LM$ portfolio delivers a value-weighted average return of 0.27% per month, with a $t$-statistic of 1.40. The corresponding equal-weighted average return amounts to 0.47% per month, with a $t$-statistic of 2.37. I note that the high-minus-low portfolio generates an average return of 0.90% per month ($t$-statistic = 2.90) for stocks in competitive industries (see Table 3.A3 in the Appendix).

## 3.4 Empirical results

In this section, I empirically test my hypothesis that the positive $LM$-return relation is stronger for firms in competitive industries.[12] To do so, I follow two complementary methodologies: an independent double-sorted portfolio approach and a cross-sectional regression approach.

### 3.4.1 Double-sorted portfolio analysis

At the end of June of each year $t$, I assign stocks to three groups using the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $HSALE$ in end-June. Independently, I also divide stocks into three groups according to the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $LM$, which is lagged 18 months, at the end of June of year $t$. The intersections of the three market competition and three labor mobility groups result in nine portfolios, which are rebalanced annually at the end of June.[13] Consequently, the transaction costs associated with implementing the trading strategy are quite low. Standard in the literature, I then obtain the value-weighted average excess returns for portfolios based on the full sample, while the equal-weighted average excess returns for each portfolio based on the all-but-microcaps sample. These average excess returns allow us to provide a comprehensive picture of the relation between labor mobility and future stock returns for firms in concentrated and competitive industries.

[12] The results based on three alternative measures of product market competition, $HSALE_{HR}$, $HAT$, and $HSALE_{HP}$, are qualitatively similar to those based on $HSALE$. To conserve space, these robustness check results are reported in the Appendix Tables 3.A4–3.A10.

[13] To establish the robustness of my baseline findings, I conduct 4×4 and 5×5 independent-sort portfolio analyses. These additional results provided in the Appendix Tables 3.A2 and 3.A3 are very similar to those reported in this subsection.

Table 3.2 summarizes the main results from the bivariate independent-sort portfolio analyses. In Panel A, which makes use of the full sample and the NYSE breakpoints to sort variables, I find that the value-weighted average monthly excess returns of $LM$-sorted portfolios in the High competition industries increase monotonically when moving from the Low labor mobility portfolio $LM_L$ to the High labor mobility portfolio $LM_H$. More importantly, the high-minus-low $LM$ portfolio generates an economically large value-weighted average monthly return of 0.83%, which is highly statistically significant, with a Newey and West (1987)-adjusted $t$-statistic of 3.05. The monthly average abnormal returns (i.e., alphas in the asset pricing models) on this spread portfolio relative to the FS, FF3, FFC, and FF5 models are also economically large and statistically distinguishable from zero; they are 0.84% ($t$-statistic = 2.96), 0.92% ($t$-statistic = 3.23), 0.69% ($t$-statistic = 2.44), and 0.83% ($t$-statistic = 2.53), respectively. Furthermore, the economic magnitude of the conditional alpha (i.e., the FS model alpha) is similar to unconditional ones (i.e., the FF3, FFC, and FF5 model alphas). This suggests somewhat of a negligible time-variation in model betas.

I observe a completely different picture for labor mobility portfolios formed in the Low competition industries (i.e., concentrated industries). The value-weighted average monthly return of −0.15% on the high-minus-low $LM$ portfolio is statistically insignificant at conventional levels ($t$-statistic = −0.91). Neither the average excess returns nor the average abnormal returns on portfolios displays a monotonically increasing pattern. For the high-minus-low $LM$ portfolio, I also see that the value-weighted average abnormal returns relative to the four asset pricing models are all negative and statistically insignificant. Specifically, the FS, FF3, FFC, and FF5 model alphas are −0.14%, −0.02%, −0.02%, and −0.02, respectively, with $t$-statistics of −0.87, −0.12, −0.13, and −0.14. All these results suggest that the positive $LM$-return relation exists only among firms in competitive industries. It is important to mention that the higher and statistically significant return of the high-minus-low $LM$ portfolio of stocks in competitive industries indicates a stronger $LM$-return relation rather than a larger variation in the $LM$ estimates. In fact, the spread in the $LM$ estimates among firms with a high $HSALE$ value in the average cross-section is 2.10, whereas it is higher at 2.72 among low $HSALE$ firms.

My empirical findings on the relation between firms' labor mobility and future stock returns in competitive industries are not sensitive to the all-but-microcaps sample analyzed in Panel B of Table 3.2. For example, the equal-weighted average monthly return on the high-minus-low $LM$ portfolio is 0.84%, which is statistically significant ($t$-statistic = 2.60). Similar to that in Panel A, the monthly average excess returns of $LM$ portfolios increase

monotonically when moving from the Low labor mobility portfolio $LM_L$ to the High labor mobility portfolio $LM_H$. Moreover, the labor mobility premium persists for firms in competitive industries even after adjusting for common risk factors using all four asset pricing models. In fact, the FS, FF3, FFC, and FF5 model alphas on the high-minus-low $LM$ portfolio are 0.79%, 0.99%, 0.64%, and 0.95% per month, respectively, with $t$-statistics of 2.23, 3.35, 2.17, and 2.68. On the contrary, the equal-weighted average return is only 0.16% ($t$-statistic = 1.31) per month for the high-minus-low $LM$-sorted portfolio formed in the Low competition industries. Likewise, the FS, FF3, FFC, and FF5 model alphas remain small in magnitude and statistically insignificant at conventional levels. Specifically, they turn out to be 0.11% ($t$-statistic = 0.90), 0.18% ($t$-statistic = 1.57), 0.12% ($t$-statistic = 0.96), and 0.19% ($t$-statistic = 1.46), respectively. Overall, these empirical results strongly support my hypothesis that the positive $LM$-return manifests itself for firms in competitive industries.

To evaluate the robustness of my preceding findings over time, I also plot the value-weighted and equal-weighted cumulative log returns on the high-minus-low $LM$ portfolios for the Low and High market competition industries in Figure 3.1. I notice that cumulative returns only on the high-minus-low $LM$ portfolio of stocks in competitive industries steadily increase throughout the sample period between July 1992 and December 2016. This suggests that the power of labor mobility to predict future stock returns persists over time only for firms in competitive industries. Taken together, the empirical results in Table 3.2 and Figure 3.1 provide significant evidence that the positive relation between labor mobility and future stock returns strengthens with the level of product market competition.

### 3.4.2 Cross-sectional regressions

A limitation of my earlier portfolio analyses is that it is difficult to include a large array of control variables when investigating the $LM$-return relation. In this subsection, I test my hypothesis by conducting the Fama and MacBeth (1973) cross-sectional regressions of monthly stock returns on labor mobility and other firm-level characteristics. Similar to that of the portfolio approach, I first sort stocks into three market competition groups according to the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $HSALE$ at the end of June of each year $t$. Then, in each month from July of year $t$ to June of year $t$+1, I run the following cross-sectional regressions for the Low and High competition industries separately:

$$R = \delta_0 + \delta_1 R_{1,1} + \delta_2 R_{12,2} + \delta_3 \ln(BM) + \delta_4 \ln(ME) + \delta_5 LM, \tag{3.2}$$

where $R$ is the monthly returns from July of year $t$ to June of year $t$+1 on an individual stock, $R_{1,1}$ is the past one-month return, $R_{12,2}$ is the past one-year return skipping the last month, $\ln(ME)$ is the natural logarithm of market value of equity, and $\ln(BM)$ is the natural logarithm of book-to-market ratio. Labor mobility, $LM$, is lagged 18 months, at the end of June of year $t$. I include $R_{1,1}$, $R_{12,2}$, $BM$, and $ME$ variables to simultaneously account for the potential effects of short-term reversal, momentum, size, and book-to-market ratio on the cross-section of average stock returns. Further, with the exception of $LM$, I winsorize all explanatory variables at the 2% level (1% in each tail of the distribution) on a monthly basis prior to running the regressions. This help reduce possible undue influence of outliers on the empirical results.

In Table 3.3, I present the time-series average slope and intercept coefficient estimates, from the cross-sectional regressions, along with their time-series $t$-statistics. To demonstrate that labor mobility premium increases with the level of market competition, I further report the time-series averages of the differences in slope and intercept coefficient estimates between the High and Low product market competition industries. In Panel A, which utilizes the full sample and the NYSE breakpoints to sort on $HSALE$, I notice that the estimated average coefficient of 0.46 ($t$-statistic = 4.50) on $LM$ for stocks in the High competition industries is much larger (both economically and statistically) than that of 0.08 ($t$-statistic = 1.30) for stocks in the Low competition industries. The average spread between the estimated slope coefficients on $LM$ for stocks in the High competition and the Low competition industries is 0.38, which is also highly statistically significant, with a $t$-statistic of 3.00.

When the all-but-microcaps sample is examined in Panel B, I find that the results are very similar to those based on the full sample in Panel A. The average coefficient estimates on $LM$ are 0.06 ($t$-statistic = 1.12) and 0.36 ($t$-statistic = 2.70), respectively, for stocks in the Low and High product market competition industries. More importantly, the estimated average slope spread of 0.30 on $LM$ is statistically significant, with a $t$-statistic of 2.07. To summarize, my results from a series of Fama and MacBeth (1973) cross-sectional regressions in Table 3.3 indicate that after controlling for the effects of firm characteristics, such as size, book-to-market ratio, momentum, and short-term reversal, the positive relation between labor mobility and future stock returns is much stronger for firms in competitive industries. In fact, the existence of a significantly positive LM-return relation for firms only in competitive industries is consistent with my previous results from the independent double-sorted portfolio analyses.

### 3.4.3 Cross-sectional regressions with market competition dummies

To further examine the relation between labor mobility and future stock returns across firms with different levels of market competition, I run the Fama and MacBeth (1973) cross-sectional regressions augmented with product market competition dummy and interaction variables. In particular, two market competition dummy variables are created by sorting stocks into three groups based on the breakpoints set to the 30th and 70th percentiles of the ranked values of $HSALE$ estimated at the end of June of each year $t$. I then estimate the following cross-sectional regressions in each month from July of year $t$ to June of year $t$+1:

$$R = \delta_0 + \delta' X, \tag{3.3}$$

$$R = \delta_0 + \delta' X + \delta_6 LM * HSALE_L + \delta_7 HSALE_L, \tag{3.4}$$

$$R = \delta_0 + \delta' X + \delta_6 LM * HSALE_H + \delta_7 HSALE_H, \tag{3.5}$$

$$R = \delta_0 + \delta' X + \delta_6 LM * HSALE_H + \delta_7 LM * HSALE_L + \delta_8 HSALE_H + \delta_9 HSALE_L, \tag{3.6}$$

where $X$ is a vector of explanatory variables including $R_{1,1}$, $R_{12,2}$, $\ln(BM)$, $\ln(ME)$, and $LM$; $HSALE_H$ ($HSALE_L$) is a dummy variable that is equal to one for stocks in the High (Low) competition industries at the end of June of each year and is zero otherwise. Analogous to Table 3.3, I winsorize all but labor mobility, $LM$, and dummy variables, $HSALE_H$ and $HSALE_L$, at the 1% and 99% levels on a monthly basis before running the Fama and MacBeth (1973) cross-sectional regressions.

I find that the results in Table 3.4 are consistent with my earlier findings based on independent double-sorted portfolio and cross-sectional regression approaches, respectively, in Sections 4.1 and 4.2. In Panel A, for the full sample and the NYSE breakpoints, when I focus on the baseline monthly cross-sectional regressions given by equation (3.3), it can be seen that $LM$ has a significantly positive relation with future stock returns. Moving to the cross-sectional regressions specified by equation (3.4), I observe that the average coefficient estimate of $-0.18$ on the interaction variable $LM * HSALE_L$ is marginally statistically significant, with a $t$-statistic of $-1.66$. The sum of the average coefficient estimates on $LM$ and $LM * HSALE_L$ is 0.07 ($t$-statistic = 1.08). This shows the absence of a significantly positive $LM$-return relation for firms in concentrated industries. Analyzing the cross-sectional regressions specified by equation (3.5), I find an estimated average coefficient on the interaction variable $LM * HSALE_H$ of 0.24, which is both economically and statistically significant at conventional levels ($t$-statistic = 2.64). Since $LM$ is standardized, the magnitude of this

coefficient implies that a one-standard deviation increase in $LM$ is associated with a 24 basis point higher future stock return per month for firms in the High competition industries relative to firms in all other groups. Also, the slope estimate of $LM$ for stocks in the High competition industries (i.e., the sum of the average coefficients on $LM$ and $LM*HSALE_H$) is 0.36, with a $t$-statistic of 3.80. For the cross-sectional regressions specified by equation (3.6), I notice that the average coefficient estimates on the interaction variables $LM * HSALE_L$ and $LM * HSALE_H$ are, respectively, $-0.08$ ($t$-statistic $= -0.69$) and 0.20 ($t$-statistic $=$ 2.01). Collectively, these results based on the full sample provide empirical evidence supportive to my hypothesis that the positive $LM$-return relation strengthens with the level of product market competition.

Turning now to the monthly cross-sectional regressions using the all-but-microcaps sample in Panel B of Table 3.4, I also find that the results are qualitatively similar to those obtained using the full sample. For example, the average coefficient estimate of 0.17 on $LM$ from the baseline cross-sectional regressions (i.e., equation (3.3)) is statistically significant ($t$-statistic $= 2.86$). For the cross-sectional regressions given by equation (3.4), the average coefficient on the interaction variable $LM * HSALE_L$ turns out to be $-0.16$ ($t$-statistic $=$ $-1.62$). Moreover, the sum of coefficient estimates on $LM$ and $LM * HSALE_L$ is $-0.07$, which is economically small and statistically insignificant, with a $t$-statistic of 1.27. All of these results suggest that labor mobility has no significantly positive effect on future stock returns for firms in concentrated industries. In the case of cross-sectional regressions specified by equation (3.5), I notice that the average coefficient estimate of 0.26 on the interaction variable $LM*HSALE_H$ is statistically significant, with a $t$-statistic of 1.98. This also means that, all else being equal, a one-standard deviation increase in $LM$ is associated with a 26 basis point higher future stock return per month for firms in the High competition industries relative to those in the Medium and Low competition industries. Notably, the sum of the average coefficient estimates on $LM$ and $LM * HSALE_H$ is 0.37, with a $t$-statistic of 2.70. Finally, in the monthly cross-sectional regressions given by equation (3.6), I notice that the average coefficient estimates on the interaction variables $LM*HSALE_L$ and $LM*HSALE_H$ are $-0.06$ ($t$-statistic $= -0.58$) and 0.24 ($t$-statistic $= 1.67$), respectively. Taken together, consistent with my hypothesis, the results in Panels A and B of Table 3.4 clearly show that the power of $LM$ to predict future stock returns is much stronger for the cross-section of firms in competitive industries.

### 3.4.4 Evidence from an extended sample

Due to the lack of availability of data on labor mobility estimates for a long period, my preceding empirical analyses are based on a restrictive sample that starts in January 1990 and ends in December 2016. Hence, a skeptic reader may argue that the findings in this chapter are specific to the relatively short sample period under analysis. In this subsection, I address this concern by reporting the results from independent double-sorted portfolio analyses as in Section 3.4.1 but using a long sample that covers the period from January 1973 to December 2016. Specifically, I follow Donangelo (2014) in this regard and extend the baseline sample backward by setting the $LM$ estimates in 1973 to 1989 equal to those estimated for 1990.[14] Overall, the results in Table 3.5 suggest a significantly positive $LM$-return relation for firms only in competitive industries, which is supportive to my hypothesis. For example, in Panel A for the full sample, the high-minus-low $LM$ portfolio in the High competition industries generates a value-weighted average monthly return of 0.39%, which is statistically significant, with a $t$-statistic of 1.97. The monthly average abnormal returns on this portfolio relative to the asset pricing models are also statistically distinguishable from zero. However, the high-minus-low $LM$ portfolio in the Low competition industries generates a statistically insignificant value-weighted average monthly return of $-0.20\%$ ($t$-statistic $= -1.48$). A qualitatively similar picture emerges for the all-but-microcaps sample, in Panel B, where the high-minus-low $LM$ portfolios delivers a statistically significant labor mobility premium only in the High competition industries. To verify the robustness of these findings, I further replicate the Fama and MacBeth (1973) regressions in Table 3.3 using the extended sample that spans January 1973 to December 2016. The results reported in Table 3.A11 of the Appendix strongly supports my hypothesis.

## 3.5 Conclusion

This chapter studies the effect of $PMC$ on the positive relation between $LM$ and stock returns, and it provides a new perspective on understanding the $LM$ premium and enriches the studies of combining labor market and asset pricing. I demonstrate comprehensive empirical tests on the hypothesis which the $LM$ premium exists only among stocks in competitive industries. The study provides an understanding of the $LM$ premium from the $PMC$ perspective. The risk of stocks with high $LM$ is more likely shifted if the stock is in a competitive industry. To conclude, my empirical results confirm that $PMC$ strengthens the

[14] To get an idea about labor mobility transition probabilities, see Table IA.XI in the Internet Appendix of Donangelo (2014).

positive $LM$-return relation. Namely, a significant portion of the $LM$ premium is explained by $PMC$.

Table 3.1: Summary statistics

The sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. There are 2718 firms in an average month. $HSALE$ is the product market competition measured by the Herfindahl-Hirschman Index (HHI), where for each industry, I first aggregate the squared net sales-based market shares of all firms in that industry in a given year and then average the HHI values over the past three years. I multiply $HSALE$ by minus one so that a higher value indicates a higher level of product market competition. $LM$ is the measure of labor mobility, which is computed in two stages, first at the occupation-level and then at the industry-level. $ME$ is the market value of equity (in million \$), which is computed as the number of shares outstanding times the absolute price of one share at the end of June of each year $t$. $BM$ is the book-to-market ratio, which is computed in June of each year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. $R_{1,1}$ is the past one-month return (in %). $R_{12,2}$ is the past one-year return (in %) skipping the last month. At the end of June of each year $t$, stocks are sorted into three portfolios based on the NYSE breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $HSALE$ ($LM$, which is lagged 18 months) at the end of June of year $t$. Panel A presents the time-series averages of the cross-sectional mean characteristics of the portfolios of firms sorted by $LM$. Panel B (Panel C) presents both the value-weighted (VW) and the equal-weighted (EW) average monthly excess returns (in %) for portfolios (quintile portfolios) sorted separately on $HSALE$ and $LM$. All portfolios are rebalanced annually at the end of June. H−L denotes a high-minus-low portfolio that is long in the High portfolio and short in the Low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016.

Panel A: Characteristics of portfolios sorted on labor mobility

| Portfolio | $HSALE$ | $ME$ | $BM$ | $R_{1,1}$ | $R_{12,2}$ |
|---|---|---|---|---|---|
| Low | −0.213 | 2946.152 | 1.059 | 1.01 | 11.30 |
| Medium | −0.178 | 3421.161 | 0.746 | 1.23 | 12.15 |
| High | −0.206 | 2740.021 | 0.739 | 1.41 | 16.10 |

Panel B: Portfolio excess returns

| | | Low | Medium | High | H−L |
|---|---|---|---|---|---|
| $HSALE$ | VW | 0.81 | 0.69 | 0.71 | −0.11 |
| | | (3.06) | (2.31) | (2.25) | (−0.57) |
| | EW | 0.90 | 1.02 | 1.09 | 0.19 |
| | | (2.45) | (2.39) | (2.36) | (0.82) |
| $LM$ | VW | 0.61 | 0.66 | 0.88 | 0.27 |
| | | (1.77) | (2.28) | (3.02) | (1.56) |
| | EW | 0.73 | 0.95 | 1.14 | 0.41 |
| | | (1.75) | (2.20) | (2.71) | (2.33) |

Panel C: Excess returns of quintile portfolios

| | | Low | 2 | 3 | 4 | High | H−L |
|---|---|---|---|---|---|---|---|
| $HSALE$ | VW | 0.77 | 0.70 | 0.74 | 0.56 | 0.85 | 0.07 |
| | | (3.02) | (2.51) | (2.47) | (1.77) | (2.47) | (0.35) |
| | EW | 0.89 | 0.90 | 0.99 | 1.09 | 1.11 | 0.22 |
| | | (2.52) | (2.12) | (2.35) | (2.57) | (2.28) | (0.83) |
| $LM$ | VW | 0.73 | 0.54 | 0.66 | 0.68 | 1.00 | 0.27 |
| | | (2.01) | (1.55) | (2.19) | (2.56) | (3.46) | (1.40) |
| | EW | 0.72 | 0.68 | 1.11 | 0.92 | 1.19 | 0.47 |
| | | (1.74) | (1.58) | (2.53) | (2.28) | (2.73) | (2.37) |

Table 3.2: Double sorts on product market competition and labor mobility

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. At the end of June of each year $t$, stocks are sorted into three groups based on the NYSE breakpoints for the bottom 30% (Low (L)), middle 40% (Medium (M)), and top 30% (High (H)) of the ranked values of product market competition at the end of June of year $t$. Product market competition for an industry is measured using net sales-based market shares of all firms in that industry. Independently, stocks are sorted into three groups based on the NYSE breakpoints for the bottom 30% (L), middle 40% (M), and top 30% (H) of the ranked values of labor mobility, which is lagged 18 months, at the end of June of year $t$. The intersections of the product market competition and labor mobility groups result in nine portfolios. All portfolios are rebalanced annually at the end of June. The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1.

| | Low competition | | | | High competition | | | |
|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_M$ | $LM_H$ | H−L | $LM_L$ | $LM_M$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.95 | 0.76 | 0.80 | −0.15 | 0.19 | 0.77 | 1.02 | 0.83 |
| | (3.15) | (2.66) | (3.10) | (−0.91) | (0.50) | (2.34) | (3.02) | (3.05) |
| FS $\alpha$ | 0.29 | 0.13 | 0.14 | −0.14 | −0.54 | 0.18 | 0.30 | 0.84 |
| | (2.01) | (0.97) | (1.29) | (−0.87) | (−2.32) | (1.05) | (1.85) | (2.96) |
| FF3 $\alpha$ | 0.22 | 0.09 | 0.20 | −0.02 | −0.54 | 0.26 | 0.38 | 0.92 |
| | (1.67) | (0.77) | (1.91) | (−0.12) | (−2.18) | (1.76) | (2.47) | (3.23) |
| FFC $\alpha$ | 0.27 | 0.15 | 0.25 | −0.02 | −0.36 | 0.44 | 0.33 | 0.69 |
| | (1.91) | (1.20) | (2.53) | (−0.13) | (−1.48) | (2.31) | (2.07) | (2.44) |
| FF5 $\alpha$ | 0.05 | 0.00 | 0.03 | −0.02 | −0.46 | 0.43 | 0.37 | 0.83 |
| | (0.37) | (0.00) | (0.25) | (−0.14) | (−1.79) | (2.25) | (2.15) | (2.53) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.77 | 0.87 | 0.93 | 0.16 | 0.49 | 0.93 | 1.33 | 0.84 |
| | (2.21) | (2.86) | (2.74) | (1.31) | (1.07) | (2.19) | (3.33) | (2.60) |
| FS $\alpha$ | 0.04 | 0.12 | 0.15 | 0.11 | −0.28 | 0.21 | 0.51 | 0.79 |
| | (0.23) | (0.61) | (0.97) | (0.90) | (−1.12) | (0.86) | (1.80) | (2.23) |
| FF3 $\alpha$ | −0.15 | 0.01 | 0.03 | 0.18 | −0.46 | 0.15 | 0.53 | 0.99 |
| | (−1.06) | (0.07) | (0.28) | (1.57) | (−2.17) | (0.88) | (3.16) | (3.35) |
| FFC $\alpha$ | 0.10 | 0.19 | 0.22 | 0.12 | −0.15 | 0.37 | 0.49 | 0.64 |
| | (0.78) | (1.33) | (2.15) | (0.96) | (−0.65) | (1.86) | (3.01) | (2.17) |
| FF5 $\alpha$ | −0.22 | −0.15 | −0.03 | 0.19 | −0.33 | 0.50 | 0.62 | 0.95 |
| | (−1.37) | (−0.95) | (−0.22) | (1.46) | (−1.18) | (2.45) | (3.78) | (2.68) |

Table 3.3: Cross-sectional regressions

The table presents the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions for different samples. At the end of June of each year $t$, stocks are sorted into three groups based on the NYSE breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of product market competition at the end of June of year $t$. Product market competition for an industry is measured using net sales-based market shares of all firms in that industry. Then in each month from July of year $t$ to June of year $t$+1 for the Low (High) competition industries, I run a cross-sectional regression of monthly return on past one-month return ($R_{1,1}$), past one-year return skipping the last month ($R_{12,2}$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), and labor mobility ($LM$), which is lagged 18 months. The full sample, in Panel A, includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample, in Panel B, excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for market competition. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low competition industries. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables (with the exception of $LM$) are winsorized at the top and bottom 1% level on a monthly basis prior to running the cross-sectional regressions. The sample period is from January 1990 to December 2016. See also notes to Table 3.1.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $LM$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.95 | 0.37 | 0.24 | 0.42 | 0.00 | 0.08 |
| | (1.79) | (0.66) | (0.56) | (4.77) | (0.09) | (1.30) |
| High | 1.77 | −1.63 | 0.07 | 0.35 | −0.11 | 0.46 |
| | (2.52) | (−3.24) | (0.24) | (3.07) | (−1.40) | (4.50) |
| High−Low | 0.83 | −2.01 | −0.17 | −0.07 | −0.11 | 0.38 |
| | (2.62) | (−3.49) | (−0.69) | (−0.84) | (−2.57) | (3.00) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 0.97 | −0.23 | 0.27 | 0.22 | −0.02 | 0.06 |
| | (1.80) | (−0.30) | (0.54) | (1.93) | (−0.48) | (1.12) |
| High | 1.49 | −1.21 | 0.21 | 0.20 | −0.06 | 0.36 |
| | (2.31) | (−1.59) | (0.58) | (1.48) | (−0.89) | (2.70) |
| High−Low | 0.52 | −0.99 | −0.06 | −0.03 | −0.04 | 0.30 |
| | (1.29) | (−1.30) | (−0.20) | (−0.27) | (−0.79) | (2.07) |

Table 3.4: Cross-sectional regressions with product market competition dummies

The table presents the time-series averages of the coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions for different samples. At the end of June of each year $t$, dummy variables are created by sorting stocks into three groups based on the NYSE breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of product market competition at the end of June of year $t$. Product market competition for an industry is measured using net sales-based market shares of all firms in that industry. Then in each month from July of year $t$ to June of year $t$+1, I run a cross-sectional regression of monthly return on past one-month return ($R_{1,1}$), past one-year return skipping the last month ($R_{12,2}$), the natural logarithm of market value of equity ($\ln(ME)$), the natural logarithm of book-to-market ratio ($\ln(BM)$), labor mobility ($LM$), and product market competition dummy and interaction variables. $HSALE_H$ ($HSALE_L$) is a dummy variable equal to one for stocks in the High (Low) competition industries in a given month and is zero otherwise. The full sample, in Panel A, includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample, in Panel B, excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables (with the exception of $LM$) are winsorized at the top and bottom 1% level on a monthly basis prior to running the cross-sectional regressions. The sample period is from January 1990 to December 2016. See also notes to Table 3.1.

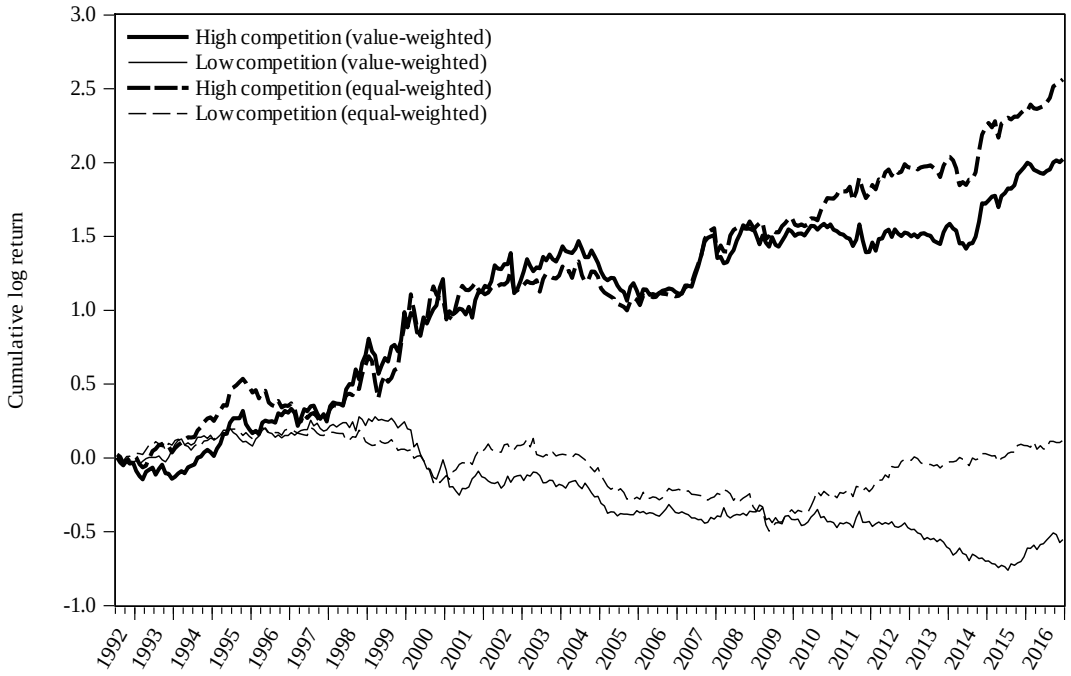
| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $LM$ | $LM * HSALE_H$ | $LM * HSALE_L$ | $HSALE_H$ | $HSALE_L$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.47 | −0.53 | 0.04 | 0.37 | −0.07 | 0.20 | | | | |
| (2.41) | (−1.18) | (0.11) | (3.29) | (−1.12) | (3.06) | | | | |
| 1.50 | −0.53 | 0.04 | 0.38 | −0.07 | 0.25 | | −0.18 | | −0.19 |
| (2.42) | (−1.20) | (0.10) | (3.55) | (−1.06) | (3.08) | | (−1.66) | | (−1.66) |
| 1.34 | −0.57 | 0.04 | 0.40 | −0.06 | 0.12 | 0.24 | | 0.26 | |
| (2.26) | (−1.28) | (0.11) | (3.99) | (−1.01) | (1.76) | (2.64) | | (2.07) | |
| 1.34 | −0.58 | 0.03 | 0.41 | −0.06 | 0.16 | 0.20 | −0.08 | 0.25 | −0.05 |
| (2.19) | (−1.31) | (0.08) | (4.12) | (−0.98) | (1.56) | (2.01) | (−0.69) | (1.97) | (−0.47) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.25 | −0.54 | 0.16 | 0.20 | −0.05 | 0.17 | | | | |
| (2.17) | (−0.82) | (0.38) | (1.59) | (−0.87) | (2.86) | | | | |
| 1.27 | −0.55 | 0.16 | 0.21 | −0.04 | 0.23 | | −0.16 | | −0.11 |
| (2.20) | (−0.84) | (0.39) | (1.78) | (−0.83) | (2.77) | | (−1.62) | | (−1.05) |
| 1.18 | −0.59 | 0.15 | 0.23 | −0.04 | 0.11 | 0.26 | | 0.15 | |
| (2.06) | (−0.91) | (0.37) | (2.01) | (−0.75) | (1.83) | (1.98) | | (1.11) | |
| 1.20 | −0.60 | 0.14 | 0.23 | −0.04 | 0.13 | 0.24 | −0.06 | 0.13 | −0.05 |
| (2.07) | (−0.94) | (0.35) | (2.07) | (−0.75) | (1.48) | (1.67) | (−0.58) | (0.95) | (−0.53) |

Table 3.5: Double sorts on product market competition and labor mobility: 1973–2016

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 3.2 except that the sample period is from January 1973 to December 2016. The labor mobility estimates in 1973 to 1989 are set equal to those estimated for 1990 as in Donangelo (2014). The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). See also notes to Tables 3.1 and 3.2.

| | Low competition | | | | High competition | | | |
|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_M$ | $LM_H$ | H−L | $LM_L$ | $LM_M$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.80 | 0.67 | 0.59 | −0.20 | 0.38 | 0.79 | 0.77 | 0.39 |
| | (3.77) | (2.85) | (2.72) | (−1.48) | (1.33) | (3.24) | (3.10) | (1.97) |
| FS $\alpha$ | 0.22 | −0.01 | −0.05 | −0.27 | −0.37 | 0.15 | 0.10 | 0.47 |
| | (2.16) | (−0.06) | (−0.49) | (−1.88) | (−2.17) | (1.27) | (0.79) | (2.30) |
| FF3 $\alpha$ | 0.14 | 0.00 | −0.01 | −0.15 | −0.34 | 0.35 | 0.21 | 0.55 |
| | (1.38) | (−0.03) | (−0.13) | (−1.07) | (−1.90) | (3.15) | (1.81) | (2.70) |
| FFC $\alpha$ | 0.22 | 0.06 | 0.04 | −0.18 | −0.16 | 0.50 | 0.23 | 0.39 |
| | (2.09) | (0.60) | (0.49) | (−1.22) | (−0.88) | (3.63) | (1.98) | (1.81) |
| FF5 $\alpha$ | 0.08 | −0.12 | −0.18 | −0.26 | −0.30 | 0.50 | 0.25 | 0.56 |
| | (0.81) | (−1.23) | (−1.89) | (−1.79) | (−1.55) | (3.31) | (1.82) | (2.25) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.77 | 0.84 | 0.77 | 0.00 | 0.58 | 0.85 | 1.09 | 0.50 |
| | (3.01) | (3.27) | (2.91) | (−0.02) | (1.90) | (2.84) | (3.61) | (2.27) |
| FS $\alpha$ | 0.04 | 0.07 | 0.01 | −0.03 | −0.20 | 0.12 | 0.31 | 0.51 |
| | (0.36) | (0.54) | (0.08) | (−0.35) | (−1.35) | (0.75) | (1.63) | (2.28) |
| FF3 $\alpha$ | −0.12 | −0.04 | −0.10 | 0.02 | −0.25 | 0.15 | 0.32 | 0.57 |
| | (−1.30) | (−0.34) | (−1.09) | (0.26) | (−1.68) | (1.18) | (2.48) | (2.68) |
| FFC $\alpha$ | 0.07 | 0.09 | 0.06 | −0.01 | 0.03 | 0.35 | 0.34 | 0.31 |
| | (0.67) | (0.80) | (0.73) | (−0.07) | (0.17) | (2.55) | (2.79) | (1.54) |
| FF5 $\alpha$ | −0.20 | −0.21 | −0.20 | 0.00 | −0.08 | 0.45 | 0.43 | 0.52 |
| | (−1.74) | (−1.82) | (−1.95) | (−0.00) | (−0.42) | (3.05) | (3.35) | (1.93) |

Figure 3.1: Returns on high-minus-low labor mobility portfolios




The figure plots the value-weighted and equal-weighted cumulative log returns on the high-minus-low labor mobility portfolios in the Low and High product market competition industries. The value-weighted portfolio returns are computed based on the full sample, whereas the equal-weighted portfolio returns are computed based on the all-but-microcaps sample. The sample spans July 1992 to December 2016. See also notes to Tables 3.1 and 3.2.

# Appendix

Table 3.A1: Summary statistics: All-but-microcaps sample

The all-but-microcaps sample excludes stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution and retains the remaining NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. There are 1148 firms in an average month. $HSALE$ is the product market competition measured by the Herfindahl-Hirschman Index (HHI), where for each industry, I first aggregate the squared net sales-based market shares of all firms in that industry in a given year and then average the HHI values over the past three years. I multiply $HSALE$ by minus one so that a higher value indicates a higher level of product market competition. $LM$ is the measure of labor mobility, which is computed in two stages, first at the occupation-level and then at the industry-level. $ME$ is the market value of equity (in million \$), which is computed as the number of shares outstanding times the absolute price of one share at the end of June of each year $t$. $BM$ is the book-to-market ratio, which is computed in June of each year $t$ as the ratio of the book value of equity at the end of the fiscal year ending in the calendar year $t-1$ to the market value of equity at the end of December in calendar year $t-1$. $R_{1,1}$ is the past one-month return (in %). $R_{12,2}$ is the past one-year return (in %) skipping the last month. At the end of June of each year $t$, stocks are sorted into three portfolios based on the breakpoints for the bottom 30% (Low), middle 40% (Medium), and top 30% (High) of the ranked values of $HSALE$ ($LM$, which is lagged 18 months) at the end of June of year $t$. Panel A presents the time-series averages of the cross-sectional mean characteristics of the portfolios of firms sorted by $LM$. Panel B (Panel C) presents both the value-weighted (VW) and the equal-weighted (EW) average monthly excess returns (in %) for portfolios (quintile portfolios) sorted separately on $HSALE$ and $LM$. All portfolios are rebalanced annually at the end of June. H−L denotes a high-minus-low portfolio that is long in the High portfolio and short in the Low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016.

Panel A: Characteristics of portfolios sorted on labor mobility

| Portfolio | $HSALE$ | $ME$ | $BM$ | $R_{1,1}$ | $R_{12,2}$ |
|---|---|---|---|---|---|
| Low | −0.211 | 5667.647 | 0.649 | 1.03 | 11.48 |
| Medium | −0.183 | 7311.736 | 0.489 | 1.12 | 12.09 |
| High | −0.213 | 5921.923 | 0.475 | 1.35 | 15.23 |

Panel B: Portfolio excess returns

| | | Low | Medium | High | H−L |
|---|---|---|---|---|---|
| $HSALE$ | VW | 0.82 | 0.69 | 0.71 | −0.11 |
| | | (3.11) | (2.33) | (2.28) | (−0.56) |
| | EW | 0.90 | 0.90 | 0.92 | 0.02 |
| | | (2.86) | (2.43) | (2.43) | (0.10) |
| $LM$ | VW | 0.62 | 0.67 | 0.88 | 0.26 |
| | | (1.80) | (2.32) | (3.05) | (1.51) |
| | EW | 0.72 | 0.79 | 1.04 | 0.31 |
| | | (1.95) | (2.20) | (3.03) | (1.92) |

Panel C: Excess returns of quintile portfolios

| | | Low | 2 | 3 | 4 | High | H−L |
|---|---|---|---|---|---|---|---|
| $HSALE$ | VW | 0.78 | 0.71 | 0.74 | 0.56 | 0.85 | 0.07 |
| | | (3.06) | (2.57) | (2.48) | (1.78) | (2.51) | (0.36) |
| | EW | 0.89 | 0.86 | 0.91 | 0.89 | 0.96 | 0.07 |
| | | (2.98) | (2.37) | (2.43) | (2.60) | (2.33) | (0.26) |
| $LM$ | VW | 0.74 | 0.55 | 0.66 | 0.68 | 1.00 | 0.26 |
| | | (2.06) | (1.59) | (2.21) | (2.60) | (3.51) | (1.33) |
| | EW | 0.85 | 0.52 | 1.00 | 0.82 | 1.07 | 0.22 |
| | | (2.21) | (1.31) | (2.72) | (2.57) | (2.98) | (1.22) |

Table 3.A2: Double sorts on product market competition and labor mobility: 4×4 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. At the end of June of each year $t$, stocks are sorted into four groups based on the NYSE breakpoints set to the 25th, 50th, and 75th percentiles the ranked values of product market competition at the end of June of year $t$. Product market competition for an industry is measured using net sales-based market shares of all firms in that industry. Independently, stocks are sorted into four groups based on the NYSE breakpoints set to the 25th, 50th, and 75th percentiles the ranked values of labor mobility, which is lagged 18 months, at the end of June of year $t$. The intersections of the product market competition and labor mobility groups result in 16 portfolios. All portfolios are rebalanced annually at the end of June. The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1 in the main chapter.

| | Low competition | | | | | High competition | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | |
| Excess return | 0.91 | 0.62 | 0.95 | 0.79 | −0.12 | 0.47 | 0.62 | 0.63 | 1.40 | 0.93 |
| | (3.07) | (2.10) | (3.17) | (3.14) | (−0.68) | (1.21) | (1.54) | (2.03) | (4.35) | (3.36) |
| FS $\alpha$ | 0.30 | 0.00 | 0.29 | 0.12 | −0.18 | −0.19 | 0.00 | −0.03 | 0.65 | 0.84 |
| | (2.03) | (−0.01) | (2.05) | (0.90) | (−0.97) | (−0.81) | (0.01) | (−0.17) | (3.95) | (2.80) |
| FF3 $\alpha$ | 0.20 | −0.01 | 0.19 | 0.23 | 0.03 | −0.29 | −0.05 | 0.17 | 0.71 | 1.00 |
| | (1.46) | (−0.09) | (1.45) | (1.85) | (0.19) | (−1.21) | (−0.26) | (0.98) | (4.64) | (3.52) |
| FFC $\alpha$ | 0.28 | 0.07 | 0.26 | 0.28 | 0.00 | −0.11 | 0.18 | 0.21 | 0.66 | 0.77 |
| | (1.88) | (0.43) | (2.12) | (2.38) | (−0.01) | (−0.50) | (0.87) | (1.18) | (4.02) | (2.77) |
| FF5 $\alpha$ | 0.05 | −0.06 | 0.10 | 0.05 | −0.01 | −0.13 | 0.20 | 0.06 | 0.69 | 0.82 |
| | (0.37) | (−0.30) | (0.74) | (0.35) | (−0.03) | (−0.52) | (0.94) | (0.31) | (4.30) | (2.57) |
| Panel B: All-but-microcaps sample | | | | | | | | | | |
| Excess return | 0.81 | 0.77 | 1.02 | 0.99 | 0.17 | 0.56 | 0.96 | 0.99 | 1.24 | 0.68 |
| | (2.42) | (2.34) | (3.29) | (2.86) | (1.25) | (1.19) | (1.97) | (2.72) | (2.81) | (1.89) |
| FS $\alpha$ | 0.08 | 0.10 | 0.24 | 0.20 | 0.11 | −0.25 | 0.20 | 0.18 | 0.42 | 0.67 |
| | (0.43) | (0.46) | (1.24) | (1.20) | (0.75) | (−0.81) | (0.68) | (0.67) | (1.38) | (1.68) |
| FF3 $\alpha$ | −0.08 | −0.10 | 0.16 | 0.09 | 0.17 | −0.38 | 0.06 | 0.20 | 0.41 | 0.79 |
| | (−0.54) | (−0.65) | (1.05) | (0.72) | (1.17) | (−1.37) | (0.30) | (0.90) | (2.29) | (2.34) |
| FFC $\alpha$ | 0.12 | 0.14 | 0.29 | 0.26 | 0.15 | −0.08 | 0.38 | 0.33 | 0.47 | 0.55 |
| | (0.82) | (0.84) | (2.09) | (2.30) | (0.94) | (−0.28) | (1.54) | (1.64) | (2.53) | (1.63) |
| FF5 $\alpha$ | −0.18 | −0.09 | −0.03 | 0.03 | 0.21 | −0.30 | 0.53 | 0.17 | 0.63 | 0.93 |
| | (−1.13) | (−0.44) | (−0.22) | (0.26) | (1.34) | (−0.91) | (2.10) | (0.70) | (3.44) | (2.34) |

Table 3.A3: Double sorts on product market competition and labor mobility: 5×5 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. At the end of June of each year $t$, stocks are sorted into five groups based on the NYSE breakpoints set to the 20th, 40th, 60th, and 80th percentiles of the ranked values of product market competition at the end of June of year $t$. Product market competition for an industry is measured using net sales-based market shares of all firms in that industry. Independently, stocks are sorted into five groups based on the NYSE breakpoints set to the 20th, 40th, 60th, and 80th percentiles the ranked values of labor mobility, which is lagged 18 months, at the end of June of year $t$. The intersections of the product market competition and labor mobility groups result in 25 portfolios. All portfolios are rebalanced annually at the end of June. The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1 in the main chapter.

| | Low competition | | | | | | High competition | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | | | |
| Excess return | 0.90 | 0.82 | 0.51 | 0.88 | 0.72 | −0.17 | 0.61 | 0.59 | 0.75 | 0.71 | 1.51 | 0.90 |
| | (2.64) | (2.48) | (1.52) | (3.07) | (2.89) | (−0.74) | (1.73) | (1.47) | (1.60) | (2.23) | (4.16) | (2.90) |
| FS $\alpha$ | 0.30 | 0.13 | −0.08 | 0.20 | 0.06 | −0.24 | −0.08 | −0.01 | −0.03 | −0.07 | 0.78 | 0.86 |
| | (1.61) | (0.59) | (−0.33) | (1.27) | (0.42) | (−1.05) | (−0.32) | (−0.03) | (−0.11) | (−0.34) | (3.17) | (2.47) |
| FF3 $\alpha$ | 0.09 | 0.18 | −0.18 | 0.16 | 0.18 | 0.09 | −0.08 | −0.04 | 0.00 | 0.20 | 0.84 | 0.93 |
| | (0.52) | (0.75) | (−0.86) | (1.04) | (1.31) | (0.41) | (−0.33) | (−0.16) | (0.01) | (1.00) | (3.57) | (2.81) |
| FFC $\alpha$ | 0.22 | 0.21 | −0.11 | 0.20 | 0.25 | 0.03 | 0.02 | 0.14 | 0.25 | 0.18 | 0.82 | 0.80 |
| | (1.16) | (0.82) | (−0.47) | (1.34) | (1.92) | (0.12) | (0.07) | (0.54) | (0.89) | (0.95) | (3.15) | (2.36) |
| FF5 $\alpha$ | −0.03 | −0.08 | −0.16 | 0.04 | 0.01 | 0.04 | −0.34 | 0.09 | 0.16 | −0.03 | 0.86 | 1.19 |
| | (−0.14) | (−0.34) | (−0.61) | (0.26) | (0.10) | (0.17) | (−1.30) | (0.30) | (0.56) | (−0.15) | (3.69) | (3.32) |
| Panel B: All-but-microcaps sample | | | | | | | | | | | | |
| Excess return | 0.90 | 0.55 | 1.00 | 1.01 | 1.03 | 0.12 | 0.25 | 0.37 | 0.88 | 0.82 | 1.25 | 1.00 |
| | (2.55) | (1.60) | (3.32) | (2.97) | (3.14) | (0.69) | (0.58) | (0.77) | (1.84) | (1.89) | (2.78) | (3.01) |
| FS $\alpha$ | 0.16 | −0.13 | 0.34 | 0.19 | 0.27 | 0.11 | −0.55 | −0.32 | 0.16 | −0.02 | 0.38 | 0.93 |
| | (0.73) | (−0.57) | (1.43) | (0.99) | (1.62) | (0.57) | (−2.25) | (−1.08) | (0.43) | (−0.06) | (1.20) | (2.58) |
| FF3 $\alpha$ | −0.02 | −0.27 | 0.17 | 0.10 | 0.15 | 0.17 | −0.67 | −0.56 | 0.09 | −0.05 | 0.40 | 1.08 |
| | (−0.10) | (−1.36) | (0.82) | (0.65) | (1.23) | (0.97) | (−2.75) | (−2.35) | (0.31) | (−0.20) | (1.87) | (3.36) |
| FFC $\alpha$ | 0.15 | −0.09 | 0.41 | 0.25 | 0.31 | 0.16 | −0.45 | −0.17 | 0.59 | 0.14 | 0.42 | 0.86 |
| | (0.79) | (−0.49) | (2.06) | (1.70) | (2.78) | (0.74) | (−1.98) | (−0.74) | (1.34) | (0.58) | (1.76) | (2.92) |
| FF5 $\alpha$ | −0.22 | −0.21 | 0.07 | −0.07 | 0.04 | 0.26 | −0.72 | −0.31 | 0.66 | 0.06 | 0.47 | 1.19 |
| | (−1.39) | (−1.01) | (0.31) | (−0.44) | (0.28) | (1.48) | (−2.78) | (−0.94) | (1.44) | (0.21) | (2.14) | (3.47) |

Table 3.A4: Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 2 of the main chapter except that product market competition, $HSALE_{HR}$, is estimated using net sales-based market shares, as per Hou and Robinson (2006). The full-sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Tables 3.1 and 3.2 in the main chapter.

| | Low competition | | | | High competition | | | |
|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_M$ | $LM_H$ | H−L | $LM_L$ | $LM_M$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | |
| Excess return | 0.88 | 0.74 | 0.82 | −0.07 | 0.34 | 0.77 | 1.02 | 0.68 |
| | (3.05) | (2.82) | (3.28) | (−0.43) | (0.91) | (2.32) | (2.99) | (2.63) |
| FS $\alpha$ | 0.26 | 0.10 | 0.14 | −0.13 | −0.36 | 0.19 | 0.28 | 0.64 |
| | (1.72) | (0.81) | (1.22) | (−0.80) | (−1.59) | (1.21) | (1.75) | (2.39) |
| FF3 $\alpha$ | 0.18 | 0.08 | 0.20 | 0.02 | −0.39 | 0.24 | 0.36 | 0.74 |
| | (1.30) | (0.70) | (1.91) | (0.13) | (−1.62) | (1.71) | (2.28) | (2.81) |
| FFC $\alpha$ | 0.26 | 0.13 | 0.27 | 0.01 | −0.22 | 0.43 | 0.31 | 0.53 |
| | (1.67) | (1.06) | (2.64) | (0.04) | (−0.91) | (2.36) | (1.98) | (1.98) |
| FF5 $\alpha$ | 0.02 | 0.02 | −0.02 | −0.03 | −0.31 | 0.42 | 0.33 | 0.64 |
| | (0.12) | (0.17) | (−0.16) | (−0.21) | (−1.25) | (2.26) | (1.88) | (2.09) |
| Panel B: All-but-microcaps sample | | | | | | | | |
| Excess return | 0.77 | 0.84 | 0.97 | 0.20 | 0.47 | 0.92 | 1.32 | 0.85 |
| | (2.44) | (2.67) | (2.88) | (1.63) | (1.01) | (2.22) | (3.29) | (2.75) |
| FS $\alpha$ | 0.04 | 0.10 | 0.19 | 0.14 | −0.29 | 0.22 | 0.50 | 0.79 |
| | (0.25) | (0.51) | (1.19) | (1.19) | (−1.13) | (0.88) | (1.79) | (2.33) |
| FF3 $\alpha$ | −0.08 | −0.05 | 0.07 | 0.15 | −0.48 | 0.17 | 0.52 | 1.00 |
| | (−0.58) | (−0.34) | (0.59) | (1.30) | (−2.32) | (0.98) | (3.16) | (3.53) |
| FFC $\alpha$ | 0.08 | 0.14 | 0.24 | 0.16 | −0.17 | 0.37 | 0.48 | 0.65 |
| | (0.63) | (1.15) | (2.42) | (1.21) | (−0.74) | (1.81) | (3.07) | (2.27) |
| FF5 $\alpha$ | −0.19 | −0.18 | −0.02 | 0.18 | −0.32 | 0.54 | 0.60 | 0.92 |
| | (−1.26) | (−1.26) | (−0.13) | (1.40) | (−1.18) | (2.62) | (3.79) | (2.70) |

Table 3.A5: Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility: 4×4 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 3.A2 except that product market competition, $HSALE_{HR}$, is estimated using net sales-based market shares, as per Hou and Robinson (2006). The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1 in the main chapter and Table 3.A2.

| | Low competition | | | | | High competition | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | |
| Excess return | 0.75 | 0.64 | 0.80 | 0.78 | 0.03 | 0.36 | 0.29 | 0.80 | 0.97 | 0.60 |
| | (2.32) | (2.11) | (2.92) | (3.26) | (0.17) | (0.97) | (0.71) | (2.71) | (2.45) | (2.32) |
| FS $\alpha$ | 0.13 | −0.05 | 0.21 | 0.13 | 0.00 | −0.29 | −0.36 | 0.15 | 0.25 | 0.54 |
| | (0.86) | (−0.26) | (1.48) | (1.03) | (−0.01) | (−1.27) | (−1.57) | (0.89) | (1.25) | (1.91) |
| FF3 $\alpha$ | −0.03 | −0.05 | 0.12 | 0.20 | 0.23 | −0.25 | −0.42 | 0.34 | 0.32 | 0.57 |
| | (−0.18) | (−0.27) | (0.94) | (1.68) | (1.28) | (−1.11) | (−2.01) | (2.12) | (2.14) | (2.19) |
| FFC $\alpha$ | 0.10 | 0.02 | 0.13 | 0.27 | 0.17 | −0.10 | −0.16 | 0.41 | 0.34 | 0.45 |
| | (0.65) | (0.09) | (1.03) | (2.42) | (0.90) | (−0.47) | (−0.75) | (2.44) | (2.25) | (1.79) |
| FF5 $\alpha$ | −0.13 | −0.19 | 0.06 | 0.00 | 0.13 | −0.26 | −0.34 | 0.36 | 0.52 | 0.78 |
| | (−0.83) | (−0.99) | (0.44) | (0.02) | (0.71) | (−1.09) | (−1.22) | (2.19) | (3.09) | (2.79) |
| Panel B: All-but-microcaps sample | | | | | | | | | | |
| Excess return | 0.79 | 0.83 | 0.97 | 0.98 | 0.19 | 0.52 | 0.98 | 0.81 | 1.24 | 0.73 |
| | (2.51) | (2.49) | (3.07) | (3.06) | (1.55) | (1.13) | (2.06) | (2.14) | (2.72) | (2.07) |
| FS $\alpha$ | 0.06 | 0.14 | 0.17 | 0.21 | 0.15 | −0.28 | 0.27 | 0.00 | 0.40 | 0.68 |
| | (0.31) | (0.64) | (0.86) | (1.28) | (1.23) | (−0.96) | (0.96) | (0.01) | (1.31) | (1.78) |
| FF3 $\alpha$ | −0.06 | −0.05 | 0.10 | 0.11 | 0.17 | −0.39 | 0.10 | 0.04 | 0.41 | 0.81 |
| | (−0.43) | (−0.35) | (0.62) | (0.96) | (1.49) | (−1.48) | (0.48) | (0.18) | (2.32) | (2.47) |
| FFC $\alpha$ | 0.08 | 0.19 | 0.23 | 0.27 | 0.18 | −0.08 | 0.43 | 0.19 | 0.49 | 0.57 |
| | (0.57) | (1.27) | (1.47) | (2.74) | (1.43) | (−0.30) | (1.82) | (0.92) | (2.70) | (1.75) |
| FF5 $\alpha$ | −0.20 | −0.06 | −0.12 | 0.01 | 0.22 | −0.31 | 0.59 | 0.09 | 0.64 | 0.95 |
| | (−1.36) | (−0.33) | (−0.76) | (0.11) | (1.80) | (−0.99) | (2.30) | (0.38) | (3.60) | (2.50) |

Table 3.A6: Double sorts on product market competition (Hou and Robinson, 2006) and labor mobility: 5×5 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 3.A3 except that product market competition, $HSALE_{HR}$, is estimated using net sales-based market shares, as per Hou and Robinson (2006). The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1 in the main chapter and Table 3.A3.

| | Low competition | | | | | | High competition | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | | | |
| Excess return | 0.82 | 0.76 | 0.58 | 0.83 | 0.92 | 0.10 | 0.71 | 0.55 | 0.77 | 0.69 | 1.44 | 0.72 |
| | (2.31) | (2.32) | (1.69) | (2.91) | (3.36) | (0.40) | (2.05) | (1.37) | (1.64) | (2.23) | (4.28) | (2.39) |
| FS $\alpha$ | 0.21 | 0.07 | −0.05 | 0.19 | 0.27 | 0.06 | 0.07 | −0.03 | 0.03 | −0.08 | 0.71 | 0.64 |
| | (1.18) | (0.32) | (−0.22) | (1.21) | (1.47) | (0.27) | (0.27) | (−0.10) | (0.11) | (−0.43) | (3.38) | (1.91) |
| FF3 $\alpha$ | 0.01 | 0.10 | −0.20 | 0.10 | 0.31 | 0.30 | 0.06 | −0.07 | 0.03 | 0.18 | 0.79 | 0.73 |
| | (0.08) | (0.45) | (−1.13) | (0.73) | (1.79) | (1.31) | (0.23) | (−0.27) | (0.11) | (0.94) | (4.27) | (2.27) |
| FFC $\alpha$ | 0.18 | 0.18 | −0.09 | 0.10 | 0.40 | 0.22 | 0.15 | 0.12 | 0.27 | 0.17 | 0.76 | 0.61 |
| | (1.01) | (0.73) | (−0.47) | (0.75) | (2.58) | (0.94) | (0.59) | (0.46) | (0.96) | (0.90) | (3.74) | (1.82) |
| FF5 $\alpha$ | −0.06 | −0.04 | −0.22 | 0.00 | 0.18 | 0.24 | −0.20 | 0.07 | 0.24 | −0.04 | 0.87 | 1.07 |
| | (−0.31) | (−0.18) | (−1.01) | (0.01) | (1.00) | (1.01) | (−0.74) | (0.23) | (0.83) | (−0.20) | (4.24) | (2.99) |
| Panel B: All-but-microcaps sample | | | | | | | | | | | | |
| Excess return | 0.79 | 0.67 | 1.00 | 0.79 | 1.03 | 0.24 | 0.38 | 0.38 | 1.03 | 0.87 | 1.17 | 0.78 |
| | (2.43) | (1.71) | (3.17) | (2.42) | (3.31) | (1.64) | (0.89) | (0.78) | (2.06) | (2.03) | (2.51) | (2.17) |
| FS $\alpha$ | 0.06 | −0.02 | 0.33 | −0.05 | 0.28 | 0.22 | −0.39 | −0.30 | 0.34 | 0.03 | 0.29 | 0.67 |
| | (0.30) | (−0.07) | (1.58) | (−0.24) | (1.64) | (1.37) | (−1.39) | (−0.96) | (0.83) | (0.10) | (0.90) | (1.76) |
| FF3 $\alpha$ | −0.08 | −0.26 | 0.14 | −0.08 | 0.18 | 0.26 | −0.53 | −0.54 | 0.29 | −0.01 | 0.32 | 0.85 |
| | (−0.49) | (−1.15) | (0.80) | (−0.48) | (1.38) | (1.71) | (−1.96) | (−2.07) | (0.93) | (−0.02) | (1.53) | (2.61) |
| FFC $\alpha$ | 0.03 | −0.03 | 0.36 | 0.02 | 0.32 | 0.30 | −0.31 | −0.12 | 0.73 | 0.18 | 0.34 | 0.65 |
| | (0.17) | (−0.16) | (2.15) | (0.13) | (2.83) | (1.88) | (−1.21) | (−0.53) | (1.61) | (0.80) | (1.51) | (2.08) |
| FF5 $\alpha$ | −0.29 | −0.17 | 0.00 | −0.32 | 0.04 | 0.33 | −0.55 | −0.31 | 0.98 | 0.12 | 0.43 | 0.98 |
| | (−1.77) | (−0.78) | (0.01) | (−2.18) | (0.33) | (2.10) | (−1.97) | (−0.86) | (2.02) | (0.46) | (1.95) | (2.79) |

Table 3.A7: Double sorts on product market competition ($HAT$) and labor mobility: 5×5 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 3.A3 except that product market competition, $HAT$, is estimated using total assets (Compustat item AT). The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2016. See also notes to Table 3.1 in the main chapter and Table 3.A3.

| | Low competition | | | | | | High competition | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | | | |
| Excess return | 0.76 | 0.89 | 0.50 | 0.80 | 0.77 | 0.01 | 0.66 | 0.66 | 0.78 | 0.65 | 1.34 | 0.69 |
| | (2.27) | (2.56) | (1.46) | (2.65) | (2.99) | (0.04) | (1.50) | (1.56) | (1.73) | (1.86) | (3.85) | (1.86) |
| FS $\alpha$ | 0.19 | 0.17 | −0.16 | 0.14 | 0.12 | −0.06 | −0.01 | 0.06 | 0.09 | −0.11 | 0.58 | 0.59 |
| | (0.98) | (0.65) | (−0.78) | (0.89) | (0.70) | (−0.26) | (−0.04) | (0.19) | (0.30) | (−0.47) | (2.67) | (1.49) |
| FF3 $\alpha$ | 0.07 | 0.21 | −0.30 | 0.03 | 0.22 | 0.14 | −0.21 | −0.03 | 0.03 | 0.16 | 0.64 | 0.85 |
| | (0.39) | (0.81) | (−1.79) | (0.20) | (1.30) | (0.58) | (−0.65) | (−0.10) | (0.12) | (0.71) | (3.41) | (2.25) |
| FFC $\alpha$ | 0.21 | 0.29 | −0.18 | 0.05 | 0.27 | 0.06 | −0.03 | 0.13 | 0.24 | 0.17 | 0.62 | 0.65 |
| | (1.13) | (1.02) | (−1.00) | (0.37) | (1.81) | (0.25) | (−0.10) | (0.46) | (0.84) | (0.79) | (3.15) | (1.73) |
| FF5 $\alpha$ | 0.05 | 0.05 | −0.36 | −0.08 | 0.06 | 0.02 | −0.23 | 0.14 | 0.13 | 0.06 | 0.65 | 0.88 |
| | (0.21) | (0.17) | (−1.62) | (−0.49) | (0.35) | (0.06) | (−0.71) | (0.45) | (0.44) | (0.26) | (2.98) | (2.21) |
| Panel B: All-but-microcaps sample | | | | | | | | | | | | |
| Excess return | 1.09 | 1.18 | 1.28 | 1.11 | 1.29 | 0.20 | 0.87 | 1.20 | 1.51 | 1.54 | 1.75 | 0.88 |
| | (3.55) | (3.07) | (3.79) | (2.92) | (4.07) | (1.19) | (1.73) | (2.40) | (3.22) | (3.77) | (3.93) | (2.27) |
| FS $\alpha$ | 0.34 | 0.49 | 0.56 | 0.20 | 0.52 | 0.18 | 0.04 | 0.62 | 0.67 | 0.71 | 0.93 | 0.89 |
| | (1.62) | (1.75) | (2.39) | (0.88) | (2.74) | (1.15) | (0.10) | (1.90) | (1.36) | (2.79) | (2.83) | (2.13) |
| FF3 $\alpha$ | 0.29 | 0.23 | 0.39 | 0.14 | 0.41 | 0.12 | −0.10 | 0.32 | 0.78 | 0.65 | 0.91 | 1.01 |
| | (1.77) | (1.06) | (1.93) | (0.73) | (2.78) | (0.69) | (−0.28) | (1.27) | (1.93) | (3.29) | (4.12) | (2.63) |
| FFC $\alpha$ | 0.37 | 0.54 | 0.61 | 0.30 | 0.54 | 0.17 | 0.13 | 0.64 | 1.33 | 0.74 | 0.96 | 0.83 |
| | (2.40) | (2.31) | (3.10) | (1.75) | (4.09) | (0.99) | (0.37) | (2.44) | (2.10) | (4.09) | (4.41) | (2.22) |
| FF5 $\alpha$ | 0.07 | 0.33 | 0.17 | −0.11 | 0.23 | 0.16 | 0.13 | 0.64 | 1.29 | 0.81 | 1.04 | 0.90 |
| | (0.45) | (1.25) | (0.86) | (−0.57) | (1.57) | (0.91) | (0.35) | (2.32) | (1.84) | (4.25) | (4.66) | (2.21) |

Table 3.A8: Double sorts on product market competition (Hoberg and Phillips, 2010) and labor mobility: 5×5 sort

The table presents the monthly excess returns and abnormal returns for portfolios sorted on product market competition and labor mobility. The setup is the same as in Table 3.A3 except that estimates of product market competition, $HSALE_{HP}$, is obtained from Hoberg and Phillips (2010). The full sample includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition and labor mobility separately. Panel A (Panel B) presents the value-weighted (equal-weighted) average monthly excess returns (in %) on portfolios. The monthly average abnormal returns ($\alpha$, in %) on portfolios are computed relative to the Ferson and Schadt (1996) conditional capital asset pricing (FS) model, the Fama and French (1993) three-factor (FF3) model, the Fama and French (1993) and Carhart (1997) four-factor (FFC) model, and the Fama and French (2015) five-factor (FF5) model. H−L is the high-minus-low portfolio. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). The sample period is from January 1990 to December 2005. See also notes to Table 3.1 in the main chapter and Table 3.A3.

| | Low competition | | | | | | High competition | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L | $LM_L$ | $LM_2$ | $LM_3$ | $LM_4$ | $LM_H$ | H−L |
| Panel A: Full sample | | | | | | | | | | | | |
| Excess return | 0.37 | 0.69 | 0.91 | 0.59 | 0.80 | 0.43 | 0.14 | 0.23 | 1.25 | −0.54 | 1.20 | 1.07 |
| | (0.93) | (2.14) | (3.22) | (1.86) | (2.21) | (1.11) | (0.28) | (0.55) | (3.36) | (−0.73) | (3.22) | (2.22) |
| FS $\alpha$ | −0.36 | 0.13 | 0.31 | −0.02 | 0.17 | 0.53 | −0.51 | −0.27 | 0.52 | −1.30 | 0.48 | 0.99 |
| | (−0.92) | (0.44) | (1.40) | (−0.09) | (0.54) | (1.23) | (−1.17) | (−0.75) | (1.67) | (−2.54) | (1.98) | (1.86) |
| FF3 $\alpha$ | −0.41 | −0.04 | 0.25 | −0.41 | −0.14 | 0.26 | −0.89 | −0.49 | 0.35 | −1.13 | 0.56 | 1.46 |
| | (−1.12) | (−0.13) | (1.20) | (−2.24) | (−0.48) | (0.58) | (−2.00) | (−1.30) | (1.14) | (−2.57) | (2.56) | (2.82) |
| FFC $\alpha$ | −0.38 | −0.04 | 0.39 | −0.26 | 0.18 | 0.56 | −0.40 | −0.04 | 0.36 | −0.61 | 0.59 | 1.00 |
| | (−1.05) | (−0.13) | (1.73) | (−1.40) | (0.68) | (1.35) | (−0.88) | (−0.12) | (1.22) | (−1.54) | (2.78) | (1.84) |
| FF5 $\alpha$ | −0.92 | −0.39 | 0.08 | −0.35 | −0.33 | 0.59 | −0.70 | 0.03 | 0.20 | −0.66 | 0.61 | 1.32 |
| | (−2.48) | (−1.29) | (0.35) | (−1.88) | (−1.04) | (1.22) | (−1.50) | (0.08) | (0.66) | (−1.65) | (2.72) | (2.41) |
| Panel B: All-but-microcaps sample | | | | | | | | | | | | |
| Excess return | 0.96 | 0.94 | 0.78 | 1.06 | 1.03 | 0.08 | 0.02 | 0.83 | 1.53 | 0.86 | 1.79 | 1.76 |
| | (2.67) | (2.93) | (2.56) | (3.17) | (3.40) | (0.33) | (0.04) | (1.75) | (3.61) | (1.71) | (3.97) | (2.84) |
| FS $\alpha$ | 0.24 | 0.33 | 0.16 | 0.37 | 0.40 | 0.16 | −0.58 | 0.13 | 0.81 | 0.10 | 0.94 | 1.52 |
| | (0.80) | (1.19) | (0.62) | (1.36) | (1.44) | (0.68) | (−1.05) | (0.44) | (2.07) | (0.32) | (2.92) | (2.29) |
| FF3 $\alpha$ | −0.07 | −0.02 | −0.25 | −0.03 | 0.04 | 0.11 | −1.03 | −0.18 | 0.47 | 0.28 | 0.95 | 1.97 |
| | (−0.31) | (−0.11) | (−1.20) | (−0.16) | (0.19) | (0.50) | (−1.90) | (−0.58) | (1.61) | (1.25) | (3.55) | (3.04) |
| FFC $\alpha$ | 0.05 | 0.10 | 0.02 | 0.13 | 0.20 | 0.14 | −0.86 | 0.37 | 0.48 | 0.54 | 0.76 | 1.61 |
| | (0.22) | (0.55) | (0.10) | (0.63) | (1.11) | (0.61) | (−1.63) | (1.31) | (1.73) | (2.27) | (2.94) | (2.59) |
| FF5 $\alpha$ | −0.35 | −0.23 | −0.46 | −0.26 | −0.10 | 0.24 | −0.86 | 0.15 | 0.26 | 0.42 | 0.89 | 1.75 |
| | (−1.60) | (−1.29) | (−2.52) | (−1.42) | (−0.56) | (1.06) | (−1.54) | (0.43) | (0.89) | (1.88) | (3.47) | (2.64) |

Table 3.A9: Cross-sectional regressions: Product market competition (Hou and Robinson, 2006)

The table presents the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions for different samples. The setup is the same as in Table 3.3 of the main chapter except that product market competition, $HSALE_{HR}$, is estimated using net sales-based market shares, as per Hou and Robinson (2006). The full sample, in Panel A, includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample, in Panel B, excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low competition industries. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables (with the exception of $LM$) are winsorized at the top and bottom 1% level on a monthly basis prior to running the cross-sectional regressions. The sample period is from January 1990 to December 2016. See also notes to Tables 3.1 and 3.3 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $LM$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 0.82 | 0.12 | 0.31 | 0.40 | 0.02 | 0.07 |
| | (1.54) | (0.22) | (0.78) | (4.71) | (0.37) | (1.19) |
| High | 1.80 | −1.32 | 0.10 | 0.35 | −0.11 | 0.32 |
| | (2.59) | (−2.65) | (0.30) | (3.14) | (−1.43) | (3.44) |
| High−Low | 0.98 | −1.44 | −0.21 | −0.05 | −0.13 | 0.25 |
| | (3.18) | (−2.28) | (−1.06) | (−0.61) | (−2.90) | (2.14) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 0.93 | −0.44 | 0.32 | 0.17 | −0.01 | 0.04 |
| | (1.68) | (−0.65) | (0.73) | (1.63) | (−0.27) | (0.70) |
| High | 1.50 | −1.19 | 0.26 | 0.20 | −0.06 | 0.40 |
| | (2.28) | (−1.52) | (0.72) | (1.54) | (−0.95) | (3.03) |
| High−Low | 0.57 | −0.75 | −0.06 | 0.03 | −0.05 | 0.35 |
| | (1.34) | (−1.05) | (−0.24) | (0.36) | (−1.01) | (2.24) |

Table 3.A10: Cross-sectional regressions with dummy variables: Product market competition (Hou and Robinson, 2006)

The table presents the time-series averages of the coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions for different samples. The setup is the same as in Table 3.4 of the main chapter except that product market competition, $HSALE_{HR}$, is estimated using net sales-based market shares, as per Hou and Robinson (2006). The full sample, in Panel A, includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample, in Panel B, excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All continuous independent variables (with the exception of $LM$) are winsorized at the top and bottom 1% level on a monthly basis prior to running the cross-sectional regressions. The sample period is from January 1990 to December 2016. See also notes to Tables 3.1 and 3.4 in the main chapter.

| Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $LM$ | $LM * HSALE_{HR,H}$ | $LM * HSALE_{HR,L}$ | $HSALE_{HR,H}$ | $HSALE_{HR,L}$ |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | | | | |
| 1.41 | −0.54 | 0.08 | 0.37 | −0.06 | 0.19 | | | | |
| (2.32) | (−1.22) | (0.22) | (3.26) | (−1.00) | (3.13) | | | | |
| 1.45 | −0.56 | 0.08 | 0.38 | −0.06 | 0.23 | | −0.15 | | −0.22 |
| (2.35) | (−1.27) | (0.22) | (3.50) | (−0.96) | (3.04) | | (−1.53) | | (−1.85) |
| 1.29 | −0.58 | 0.08 | 0.40 | −0.06 | 0.11 | 0.24 | | 0.26 | |
| (2.20) | (−1.33) | (0.22) | (4.00) | (−0.90) | (1.77) | (2.59) | | (2.00) | |
| 1.31 | −0.59 | 0.07 | 0.40 | −0.05 | 0.14 | 0.22 | −0.06 | 0.24 | −0.10 |
| (2.17) | (−1.35) | (0.20) | (4.14) | (−0.88) | (1.52) | (2.21) | (−0.52) | (1.81) | (−0.99) |
| Panel B: All-but-microcaps sample | | | | | | | | | |
| 1.28 | −0.60 | 0.18 | 0.18 | −0.05 | 0.16 | | | | |
| (2.24) | (−0.90) | (0.44) | (1.45) | (−0.99) | (2.83) | | | | |
| 1.31 | −0.63 | 0.19 | 0.19 | −0.05 | 0.23 | | −0.17 | | −0.10 |
| (2.25) | (−0.97) | (0.46) | (1.65) | (−0.96) | (2.72) | | (−1.51) | | (−0.91) |
| 1.22 | −0.65 | 0.18 | 0.20 | −0.04 | 0.10 | 0.30 | | 0.12 | |
| (2.14) | (−1.00) | (0.43) | (1.85) | (−0.89) | (1.71) | (2.29) | | (0.85) | |
| 1.25 | −0.67 | 0.17 | 0.21 | −0.04 | 0.13 | 0.27 | −0.07 | 0.10 | −0.05 |
| (2.14) | (−1.06) | (0.43) | (1.92) | (−0.90) | (1.47) | (2.10) | (−0.62) | (0.73) | (−0.54) |

Table 3.A11: Cross-sectional regressions: 1973–2016

The table presents the time-series average slope and intercept coefficient estimates from the Fama and MacBeth (1973) cross-sectional regressions for different samples. The setup is the same as in Table 3.3 of the main chapter except that the sample period is from January 1973 to December 2016. The labor mobility estimates in 1973 to 1989 are set equal to those estimated for 1990 as in Donangelo (2014). The full sample, in Panel A, includes all NYSE/AMEX/NASDAQ-listed nonfinancial and nonregulated ordinary common stocks with both nonmissing product market competition and labor mobility estimates in a given year $t$. The all-but-microcaps sample, in Panel B, excludes stocks with an end-June market value of equity below the 20th percentile of the NYSE market capitalization distribution and the remaining stocks are used to compute the breakpoints for product market competition. High−Low is the time-series average of the differences in slope or intercept coefficient estimate between the High and Low competition industries. Numbers in parentheses are $t$-statistics adjusted following Newey and West (1987). All independent variables (with the exception of $LM$) are winsorized at the top and bottom 1% level on a monthly basis prior to running the cross-sectional regressions. See also notes to Tables 3.1 and 3.3 in the main chapter.

| | Intercept | $R_{1,1}$ | $R_{12,2}$ | $\ln(BM)$ | $\ln(ME)$ | $LM$ |
|---|---|---|---|---|---|---|
| Panel A: Full sample | | | | | | |
| Low | 1.55 | −1.00 | 0.50 | 0.36 | −0.08 | 0.01 |
| | (3.83) | (−2.18) | (1.87) | (4.71) | (−1.95) | (0.17) |
| High | 2.07 | −1.93 | 0.34 | 0.22 | −0.15 | 0.25 |
| | (4.10) | (−4.65) | (1.68) | (2.60) | (−2.68) | (3.33) |
| High−Low | 0.52 | −0.93 | −0.16 | −0.14 | −0.07 | 0.24 |
| | (2.32) | (−1.69) | (−0.96) | (−2.03) | (−2.16) | (2.83) |
| Panel B: All-but-microcaps sample | | | | | | |
| Low | 1.26 | −0.37 | 0.68 | 0.24 | −0.05 | 0.00 |
| | (3.07) | (−0.65) | (2.15) | (2.67) | (−1.27) | (−0.03) |
| High | 1.43 | −1.12 | 0.74 | 0.17 | −0.05 | 0.21 |
| | (3.00) | (−1.95) | (2.79) | (1.75) | (−0.93) | (2.39) |
| High−Low | 0.17 | −0.75 | 0.06 | −0.06 | 0.00 | 0.21 |
| | (0.61) | (−1.10) | (0.30) | (−0.83) | (0.01) | (2.26) |

# Concluding Remarks

The first chapter of this thesis compares the performance of ten different asset pricing models in explaining the average excess returns on various sets of prominent anomaly portfolios. My list of models comprises the capital asset pricing model of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (1993) and Carhart (1997) four-factor model, the Fama and French (1993) and Pástor and Stambaugh (2003) four-factor model, the Asness and Frazzini (2013) three-factor model, the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, the Stambaugh and Yuan (2016) four-factor model, and the Barillas and Shanken (2018) six-factor model. An informal analysis based on a comprehensive set of performance metrics in the time-series domain shows that the Stambaugh and Yuan (2016) four-factor model provides the best, though still incomplete, description of average monthly excess returns on a majority of my test asset portfolios. The Hou, Xue, and Zhang (2015) $q$-factor model takes second place, while the Fama and French (2015) five-factor model and the Barillas and Shanken (2018) six-factor model jointly take third place in the horse race.

However, a different picture emerges when the relative performance of all the models is tested statistically using the pairwise cross-sectional regression $R^2$ equality test and the multiple model comparison test. I find that the Hou, Xue, and Zhang (2015) $q$-factor model, the Fama and French (2015) five-factor model, the four-factor model of Fama and French (2015) that drops the value factor, and the Barillas and Shanken (2018) six-factor model perform about equally well and take equal first place. The Stambaugh and Yuan (2016) four-factor model, which is the top performer in the time-series regressions, turns out to be the next best model. Unlike previous empirical studies, I also find that the capital asset pricing model of Sharpe (1964) and Lintner (1965) performs reasonably well. My cross-sectional findings remain robust irrespective of regression methodologies and sequential tests for nonnested models. All these results also indicate that the common practice of identifying the superior model(s) by informally comparing pricing performance metrics can sometimes be mislead-

ing. Taken together, my empirical findings have important implications for practitioners who need to evaluate capital budgeting, equity valuation, investment management, and fund performance.

The second chapter investigates the effect of illiquidity on the relation between R&D investment and expected equity returns. Based on a simple model of R&D venture, I develop a testable hypothesis that the positive R&D-return relation strengthens with level of stock illiquidity. An R&D firm lacking sufficient internal resources but wishing to continue the project issues outside financial claims to investors who may face liquidity problems before successful completion of the project. If the market is perfectly liquid and investors can sell their stocks instantaneously, then this would not matter much. However, in the presence of asymmetric information, investors or dealers who would be willing to buy such stocks might find it harder to decipher whether this sale is triggered by a cash constrained liquidity trader or by an informed trader selling upon receiving bad news about the R&D project. This results in further increases in the R&D premium to outside investors, which forces the firm to wrap up the project earlier, due to increased project costs (i.e., due to illiquidity) associated with external financing. Moreover, this illiquidity-induced reduction in project duration increases the likelihood of failure of the project due to its hurried completion. As a result, R&D-intensive firms' risk increases with their degree of stock illiquidity.

Consistent with the theoretical model's prediction, I find robust empirical evidence that the positive R&D-return relation exists among illiquid stocks. A further analysis indicates that the important role of illiquidity in the relation between R&D intensity and future stock returns cannot be explained by factors such as financial constraints, innovation ability, and product market competition, which have been shown to affect the R&D premium in prior studies. All these results suggest that stock illiquidity is an independent driver of the positive R&D-return relation. This chapter thereby complements and extends the extant literature by providing an understanding of the R&D investment premium from the perspective of a firm's stock illiquidity.

The third chapter studies the effect of product market competition on the positive relation between labor mobility and stock returns, and it provides a new perspective on understanding the labor mobility premium and enriches the studies of combining labor market and asset pricing. I demonstrate comprehensive empirical tests on the hypothesis which the labor mobility premium exists only among stocks in competitive industries. The study provides an understanding of the labor mobility premium from the product market competition perspec-

tive. The risk of stocks with high labor mobility is more likely shifted if the stock is in a competitive industry. To conclude, my empirical results confirm that product market competition strengths the positive labor mobility-return relation. Namely, a significant portion of the labor mobility premium is explained by product market competition.

# Bibliography


Aboody, David, and Baruch Lev, 2000, Information asymmetry, R&D, and insider gains, *Journal of Finance* 55, 2747–2766.

Amihud, Yakub, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov, Allaudeen Hameed, Wenjin Kang, and Huiping Zhang, 2015, The illiquidity premium: International evidence, *Journal of Financial Economics* 117, 350–368.

Amihud, Yakub, and Haim Mendelson, 1989, The effects of beta, bid-ask spread, residual risk, and size on stock returns, *Journal of Finance* 44, 479–486.

Ang, Andrew, 2014, *Asset Management: A Systematic Approach to Factor Investing* (Oxford University Press, New York).

——— , Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Asness, Clifford, and Andrea Frazzini, 2013, The devil in HML's details, *Journal of Portfolio Management* 39, 49–68.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Bali, Turan G., Robert F. Engle, and Scott Murray, 2016, *Empirical Asset Pricing: The Cross Section of Stock Returns* (John Wiley & Sons, Inc., New Jersey).

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri V. Nikolaev, 2015, Deflating profitability, *Journal of Financial Economics* 117, 225–248.

Barillas, Francisco, Raymond Kan, Cesare Robotti, and Jay Shanken, 2017, Model comparison with Sharpe ratios, Working Paper, Goizueta Business School, Emory University, Georgia.

Barillas, Francisco, and Jay Shanken, 2017, Which Alpha?, *Review of Financial Studies* 30, 1316–1338.

——— , 2018, Comparing asset pricing models, *Journal of Finance* 73, 715–754.

Beber, Alessandro, and Marco Pagano, 2013, Short-selling bans around the world: Evidence from the 2007–09 crisis, *Journal of Finance* 68, 343–381.

Belo, Frederico, Jun Li, Xiaoji Lin, and Xiaofei Zhao, 2017, Labor-force heterogeneity and asset prices: The importance of skilled labor, *Review of Financial Studies* 30, 3669–3709.

Belo, Frederico, Xiaoji Lin, and Santiago Bazdresch, 2014, Labor hiring, investment, and stock return predictability in the cross section, *Journal of Political Economy* 122, 129–177.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.

——— , 2004, Valuation and return dynamics of new ventures, *Review of Financial Studies* 17, 1–35.

Bharath, Sreedhar T., and Tyler Shumway, 2008, Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339–1369.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: Some empirical tests, in Michael C. Jensen, ed.: *Studies in the Theory of Capital Markets* . pp. 79–121 (Praeger: New York).

Blundell, Richard, Rachel Griffith, and John Van Reenen, 1999, Market share, market value and innovation in a panel of british manufacturing firms, *Review of Economic Studies* 66, 529–554.

Brealey, Richard A., Stewart C. Myers, and Franklin Allen, 2016, *Principles of Corporate Finance* (McGraw-Hill Education, New York).

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen, 2009, Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom, *Journal of Finance* 64, 151–185.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Carpenter, Robert E., and Bruce C. Petersen, 2002, Capital market imperfections, high-tech investment, and new equity financing, *Economic Journal* 112, 54–72.

Chambers, Dennis, Ross Jennings, and Robert B. Thompson, 2002, Excess returns to R&D-intensive firms, *Review of Accounting Studies* 7, 133–158.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431–2456.

Chan, Su Han, John D. Martin, and John W. Kensinger, 1990, Corporate research and development expenditures and share value, *Journal of Financial Economics* 26, 255–276.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2008, Liquidity and market efficiency, *Journal of Financial Economics* 87, 249–268.

——— , 2011, Recent trends in trading activity and market quality, *Journal of Financial Economics* 101, 243–263.

Cochrane, John H., 2005, *Asset Pricing* (Princeton University Press, New Jersey).

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *Review of Financial Studies* 26, 635–666.

Danthine, Jean-Pierre, and John B. Donaldson, 2002, Labour relations and asset returns, *Review of Economic Studies* 69, 41–64.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Donangelo, Andrés, 2014, Labor mobility: Implications for asset pricing, *Journal of Finance* 69, 1321–1346.

——— , Francois Gourio, Matthias Kehrig, and Miguel Palacios, 2017, The cross-section of labor leverage and equity returns, Working Paper, University of Texas at Austin.

Eberhart, Allan C., William F. Maxwell, and Akhtar R. Siddique, 2004, An examination of long-term abnormal stock returns and operating performance following R&D increases, *Journal of Finance* 59, 623–650.

Eiling, Esther, 2013, Industry-specific human capital, idiosyncratic risk, and the cross-section of expected stock returns, *Journal of Finance* 68, 43–84.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

——— , and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

——— , 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

——— , 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

——— , 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

——— , 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

——— , 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915–1947.

——— , 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472.

——— , 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

——— , 2016, Dissecting anomalies with a five-factor model, *Review of Financial Studies* 29, 69–103.

——— , 2017, Choosing factors, Working Paper, Booth School of Business, University of Chicago, Illinois.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu, 2017, Taming the factor zoo, Working Paper, Yale School of Management, Yale University, Connecticut.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.

Fischer, Bernd R., and Russ Wermers, 2012, *Performance Evaluation and Attribution of Security Portfolios* (Academic Press).

Frazzini, Andrea, and Lasse H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24–37.

Gao, Xiaohui, and Jay R. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics* 97, 33–52.

Geroski, Paul A, et al., 1995, Market structure, corporate performance, and innovative activity, *OUP Catalogue*.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Giroud, Xavier, and Holger M. Mueller, 2011, Corporate governance, product market competition, and equity prices, *Journal of Finance* 66, 563–600.

Gitman, Lawrence J., and Vincent A. Mercurio, 1982, Cost of capital techniques used by major U.S. firms: Survey and analysis of Fortune's 1000, *Financial Management* 14, 21–29.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Gospodinov, Nikolay, Raymond Kan, and Cesare Robotti, 2013, Chi-squared tests for evaluation and comparison of asset pricing models, *Journal of Econometrics* 173, 108–125.

Goyenko, Ruslan Y., Craig W. Holden, and Charles A. Trzcinka, 2009, Do liquidity measures measure liquidity?, *Journal of Financial Economics* 92, 153–181.

Graham, John R., and Campbell R. Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.

Green, Jeremiah, John R. M. Hand, and X. Frank Zhang, 2014, The remarkable multidimensionality in the cross-section of expected U.S. stock returns, Working Paper, Yale School of Management, Yale University, Connecticut.

Grinold, Richard C., and Ronald N. Kahn, 1995, *Active Portfolio Management: Quantitative Theory and Applications* (McGraw-Hill Education, New York).

Grossman, Gene M., and Carl Shapiro, 1987, Dynamic R&D competition, *Economic Journal* 97, 372–387.

Gu, Lifeng, 2016, Product market competition, R&D investment, and stock returns, *Journal of Financial Economics* 119, 441–455.

Guadalupe, Maria, 2007, Product market competition, returns to skill, and wage inequality, *Journal of Labor Economics* 25, 439–474.

Hadlock, Charles J., and Joshua R. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ index, *Review of Financial Studies* 23, 1909–1940.

Hall, Bronwyn H., 1996, The private and social returns to research and development, in Bruce L. R. Smith, and Claude E. Barfield, ed.: *Technology, R&D, and the Economy* . pp. 140–183 (Brookings Institution Press: Washington, D.C.).

——— , 2002, The financing of research and development, *Oxford Review of Economic Policy* 18, 35–51.

Hameed, Allaudeen, Wenjin Kang, and Sathish Viswanathanan, 2010, Stock market declines and liquidity, *Journal of Finance* 65, 257–293.

Han, Yufeng, and David Lesmond, 2011, Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, *Review of Financial Studies* 24, 1590–1629.

Harvey, Campbell R., and Yan Liu, 2017, Lucky factors, Working Paper, Fuqua School of Business, Duke University, North Carolina.

——— , and Heqing Zhu, 2016, . . . and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632–654.

——— , 2017, Innovative originality, profitability, and stock returns, Working Paper, Paul Merage School of Business, University of California, Irvine.

——— , 2018, Innovative originality, profitability, and stock returns, *Review of Financial Studies* 31, 2553–2605.

Hoberg, Gerard, and Gordon Phillips, 2010, Real and financial industry booms and busts, *Journal of Finance* 65, 45–86.

Hou, Kewei, G. Andrew Karolyi, and Bong-Chan Kho, 2011, What factors drive global stock returns?, *Review of Financial Studies* 24, 2527–2574.

Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *Journal of Finance* 61, 1927–1956.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

——— , 2017a, A comparison of new factor models, Working Paper, Fisher College of Business, Ohio State University, Ohio.

——— , 2017b, Replicating anomalies, Working Paper, Fisher College of Business, Ohio State University, Ohio.

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Jagannathan, Ravi, and Iwan Meier, 2002, Do we need CAPM for capital budgeting?, *Financial Management* Winter, 5–27.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

Kan, Raymond, and Cesare Robotti, 2009, Model comparison using the Hansen-Jagannathan distance, *Review of Financial Studies* 22, 3449–3490.

——— , and Jay Shanken, 2013, Pricing model performance and the two-pass cross-sectional regression methodology, *Journal of Finance* 68, 2617–2649.

Kandel, Shmuel, and Robert F. Stambaugh, 1995, Portfolio inefficiency and the cross-section of expected returns, *Journal of Finance* 50, 157–184.

Kaplan, Steven N., and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *Quarterly Journal of Economics* 112, 169–215.

Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25, 1366–1413.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2017, Interpreting factor models, *Journal of Finance (forthcoming)*.

Kuehn, Lars-Alexander, Mikhail Simutin, and Jessie J. Wang, 2017, A labor capital asset pricing model, *Journal of Finance* 72, 2131–2178.

Kumar, Praveen, and Dongmei Li, 2016, Capital investment, innovative capacity, and stock returns, *Journal of Finance* 71, 2059–2094.

Lamont, Owen, Christopher Polk, and Jesús Saá-Requejo, 2001, Financial constraints and stock returns, *Review of Financial Studies* 14, 529–554.

Lehmann, Bruce N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1–28.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21, 107–138.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

Li, Dongmei, 2011, Financial constraints, R&D investment, and stock returns, *Review of Financial Studies* 24, 2974–3007.

Lin, Xiaoji, 2012, Endogenous technological progress and the cross-section of stock returns, *Journal of Financial Economics* 103, 411–427.

Linnainmaa, Juhani T., and Michael R. Roberts, 2016, The history of the cross-section of stock returns, Working Paper, Wharton School, University of Pennsylvania, Pennsylvania.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

McLean, David R., and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Merz, Monika, and Eran Yashiv, 2007, Labor and the market value of the firm, *American Economic Review* 97, 1419–1431.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Nickell, Stephen J, 1996, Competition and corporate performance, *Journal of Political Economy* 104, 724–746.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Penman, Stephen H., and Xiao-Jun Zhang, 2002, Accounting conservatism, the quality of earnings, and stock returns, *Accounting Review* 77, 237–264.

Santos, Tano, and Pietro Veronesi, 2005, Labor income and predictable stock returns, *Review of Financial Studies* 19, 1–44.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289–315.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, *Journal of Finance* 70, 1903–1948.

Stambaugh, Robert F., and Yu Yuan, 2016, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

Valta, Philip, 2012, Competition and the cost of debt, *Journal of Financial Economics* 105, 661–682.

Vuong, Quang H., 1989, Likelihood ratio tests for model selection and non-nested hypotheses, *Econometrica* 57, 307–333.

Whited, Toni M., and Guojun Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531–559.

Xing, Yuhang, 2008, Interpreting the value effect through the $q$-theory: An empirical investigation, *Review of Financial Studies* 21, 1767–1795.