

Three Essays in Intraday Momentum, Market Efficiency and Market Liquidity

by

Ali Shakil Khan

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Declaration

I declare that this thesis was completed during my PhD study at the University of Nottingham. This thesis or part thereof has not been submitted for a degree at any other University.

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Abstract

This thesis is composed of three essays which aim to provide a better understanding of intraday market momentum, market efficiency and market liquidity in international markets. These aspects are under researched in international stock markets, particularly in the Chinese stock markets. These issues have become significant as the International markets continue to expand in size and some of them such as China differ considerably in terms of ownership structure, have various share classes and are subject to various trading regulations.

In the first chapter, we employ an empirical analysis to examine the existence of a well documented [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum pattern (which has also been verified and modelled by [Bogousslavsky \(2016\)](#)) in the cross section of US stock returns for Chinese stock returns. While the stocks in UK and Brazil exhibit the presence of the intraday momentum pattern, we don't find evidence of this pattern in the Chinese A-shares market. The pattern exhibits itself in the Chinese B-shares much more profoundly than the dual listed A-share counterparts. Since the only significant difference between the Chinese dual listed A-shares and B-shares is investor composition; we conclude that investor composition is important in explaining the [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum pattern. Further examination of dual listed A-shares in China and H-shares in Hong Kong suggests that limits of arbitrage such as price limits have an adverse impact on the proliferation of the pattern as these inhibit the ability of investors to exploit the [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum strategy. Our results also show that domestic Chinese investors are contrarians and engage in contrarian strategies on an intraday basis and short-term return reversals last for 60 to 90 minutes in Chinese markets.

In chapter two, I consider the entire sample of Chinese stocks and empirically test the intraday market efficiency by employing two widely used measures - the intraday return predictability measure and the variance ratio measure. We find that limits of arbitrage

play a major role in facilitating market efficiency. We also document a time of the day effect in market efficiency. The first half hour of trading exhibits the highest bid-ask spreads and the highest level of inefficiency in terms of the deviation from unity in the variance ratio tests conducted for two alternative specifications to ensure robustness. This information is vital for investors as they would be able to time their trades better with this information. We use two exogenous shocks to limits of arbitrage- the advent of Shenzhen connect (which increases trade volume) and lowers limits of arbitrage and the inclusion of A-shares in the MSCI emerging markets index (which also increases trade volume and investments in Chinese A-shares) to study their impacts on market efficiency. Our results indicate that both these events improve market efficiency in terms of both our measures. Therefore, we conclude that policy makers in China are acting in the right direction to elevate China's status in world markets by adapting policies that are inherently making China more attractive to global investors by enhancing market efficiency.

The third chapter is an investigation in to the relationship between economic, political and trade policy uncertainties and stock liquidity. I employ a panel regression and event study regression methodology to examine the role of economic and trade policy uncertainty in driving stock liquidity by taking the monthly average of two widely used liquidity measures- transaction costs and price impact measure. The time period spans from 1996 to 2018 and our results show that the higher the level of economic and trade policy uncertainty, the higher the level of illiquidity or the lower the level of liquidity. We further exploit the Bo political scandal in China to study the impact of political uncertainty and the break out of the trade war between the US and China to employ an event study methodology to study the impact of these two events on liquidity. We see that both the event studies indicate that both political and trade uncertainty inhibit stock liquidity, particularly for the more policy or trade sensitive industries. We also use high frequency data and two market efficiency measures- the the return predictability measure and the variance ratio tests to determine the impact of trade policy uncertainty on market efficiency. Our findings further indicate that trade policy uncertainty has a detrimental impact on market efficiency.

Introduction to the Thesis

This thesis provides an in-depth investigation of some of the most important phenomenon in Finance such as momentum, market efficiency and market liquidity with particular focus on Chinese stock markets. Some of the findings are different from the classical findings observed in developed markets such as the United States while some provide evidence that challenge the notion of Chinese markets being a ‘casino’.¹ I include some very recent and significant events such as US-China trade war, MSCI inclusion of A-shares, Shenzhen stock connect, Bo political scandal etcetera and examine their impact on intraday momentum, market efficiency and market liquidity. Our findings will highlight unique market aspects in one of the most rapidly evolving and growing stock markets in the world.

In Chapter One, we test for the existence of a prominent intraday momentum pattern first documented by [Heston, Korajczyk, and Sadka \(2010\)](#) and further modelled and explained by [Bogousslavsky \(2016\)](#) in China, the UK and Brazil. Ever since the seminal study [Jegadeesh and Titman \(1993\)](#) first documented momentum profits on a momentum strategy that went long on past winners and short on past losers based on monthly performance (ranging from 3 to 12 months for the subsequent 3-12 month periods), there has been an explosion of research in the area of momentum. The momentum strategy is now as prominent as the size and the value strategies. [Jegadeesh and Titman \(2001\)](#) further test their results documented in their seminal study [Jegadeesh and Titman \(1993\)](#) and find that the strategy stands the test of time and using an out of sample estimation conclude that the profits from a momentum strategy are not the result of data snooping.

While momentum has been well documented in the US stock markets, there have been studies that have found its existence in Asian stock markets as being weak or non-existent. For instance, [Fama and French \(2012\)](#) find that momentum doesn’t exist in Japan, but provide international evidence on the existence of the phenomenon. [Chui, Titman, and Wei \(2010\)](#) provide evidence that momentum is weaker in countries with low levels of

¹See the Economist news article :<https://www.economist.com/free-exchange/2015/05/26/a-crazy-casino>

individualism and it offers an explanation of why East Asian countries demonstrate the weakest momentum profits. Both [Fama and French \(2012\)](#) and [Chui, Titman, and Wei \(2010\)](#) offer a behavioural explanation to back the absence and or lack of momentum in Japan and East Asian countries respectively. Furthermore, [Jegadeesh and Titman \(2001\)](#) also use a behavioural model to explain the existence of the momentum phenomenon in developed markets such as the United States.

[Chui and Titman \(2017a\)](#) further try to unravel the behavioural dynamics that lead to weaker momentum in East Asian markets by using dual listed A-shares and B-shares which have different investor composition. The A-shares are dominated by retail/individual investors, whereas, the B-shares are mostly foreign sophisticated institutional investors. The findings of [Chui and Titman \(2017a\)](#) indicate that momentum is much stronger in class B-shares as compared to class A-shares owing to difference in trading behaviours between the two distinct types of investors who own the shares- retail versus institutional.

While a lot of international studies have been done to examine the momentum phenomenon based on daily or monthly returns. There is a vacuum in terms of any international study examining the [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum pattern. This intraday momentum pattern arises when a long short portfolio based on winners and losers during any particular half hour interval of the day provides profits during the same half hour interval the following day and for up to forty consecutive days. In Chapter One, we examine this phenomenon in China, the UK and Brazil. We choose the UK and Brazil along with China because both are international markets outside the US and one is more comparable to China in terms of market capitalization and is outside Asia (the UK), while the other is an emerging market (Brazil).

We follow the methodology employed by [Heston, Korajczyk, and Sadka \(2010\)](#) and perform cross-sectional regressions of current half-hour interval returns on lagged half-hour returns during the same daily interval for up to 40 days. The coefficients are then averaged over time as per the [Fama and MacBeth \(1973\)](#) approach . This analyses indicates that the regression coefficients are more significant both economically and statistically for the UK and Brazil as compared to China. This is the first evidence that shows the weaker proliferation of the pattern in China. We also perform a portfolio analyses based on the formulation of a long short portfolio formation in line with [Heston, Korajczyk, and Sadka \(2010\)](#) based on each half hour intervals returns containing only the top and bottom deciles. These portfolio returns for China also turn out to be significantly weaker as compared to the UK and Brazil.

We then conduct the cross sectional regression analysis and the portfolio analysis on dual listed Chinese A-shares and B-shares. Our findings lead us to conclude that the intraday momentum effect is much stronger in B-shares. This makes us conclude that difference in investor composition between A-shares and their dual listed B-shares is the driver of this effect. We then exploit the inclusion of 232 A-shares in the MSCI index and conduct our analysis in the pre and post inclusion environments and document a significant increase in the momentum effect among the included shares post inclusion. We also document an increase in foreign and institutional ownership of the stocks during the post inclusion period and attribute the momentum effect to the increased participation of institutional owners in the 232 A-shares that were included in the MSCI index.

Our findings show how the Chinese market is different as compared to the US, UK and Brazil in terms of the proliferation of the [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum pattern. Furthermore, they support earlier findings by [Campbell, Ramadorai, and Schwartz \(2009\)](#) who document that institutional investor are highly persistent in their trading and by [Kaniel, Saar, and Titman \(2008\)](#) who document that individual investors are contrarians. Also, Chapter One highlights how the steps by the Chinese Regulators to reform the market have lead to the inclusion of stocks in the MSCI index and this has lead to the institutionalisation of the Chinese markets. It serves as a testament to the positive impact of the policy reforms being undertaken to improve the Chinese market. A future avenue for research is to further study changes in the momentum pattern upon further and broader inclusion of shares in the MSCI index.

Recent developments such as MSCI inclusion of Chinese A-shares in its index and further plans to expand inclusion of medium and small corporations to the index are evidence that the paradigm is shifting in Chinese markets and they are becoming increasingly efficient. My second chapter aims to challenge the perception that the Chinese market is a ‘casino’.

In Chapter Two, we set out to test intraday market efficiency in the Chinese stock market based on the entire market and not just based on a small sample of stocks. It is critical to empirically test the intraday market efficiency in Chinese markets as existing evidence on the level of efficiency in Chinese markets is limited to either daily or monthly data, intraday efficiency studies either consider a small sample of firms or rely on one particular measure of efficiency. We provide intraday evidence on market efficiency in China using two widely used intraday efficiency measures- the intraday return predictability measure and the variance ratio tests. These measures are time tested measures developed and em-

ployed by seminal studies like [Chordia, Roll, and Subrahmanyam \(2005\)](#) and most recently employed by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#). These findings will be of particular interest to investors who are eager to invest in one of the fastest growing economies in the world. It will also enable policy makers to better understand and mitigate any potential obstructions in the way of market efficiency.

Furthermore, in chapter two, we also include a Limits of Arbitrage Index ([Gu, Kang, and Xu \(2018\)](#)) and based on the average daily index value of each stock during the sample period we segregate the stocks in to five groups based on their average index values. We show that higher limits of arbitrage contribute considerably to market inefficiency and provide valuable insights to both policy makers and investors to anticipate and potentially mitigate the adverse impact of them on market efficiency. This study demonstrates that if policy makers can reduce the limits of arbitrage by including more stocks in the Marginal Trading and Short Selling (MTSS) program, providing futures contracts to hedge against adverse price movements as offered to stocks under the China Securities Index 300 (CSI 300) and easing price limits they can improve market efficiency which in turn will increase investor confidence and make it easier for the firms to raise capital.

We also employ an event study methodology as employed by [Chang, Luo, and Ren \(2014\)](#) to study the impact of inclusion in the MSCI index on market efficiency of included stocks. Our results indicate that there is an improvement in the efficiency of added stocks. This gives evidence on additional benefits of institutional investors who play a bigger role post inclusion in the MSCI index included stocks and provide additional liquidity thereby, lowering limits of arbitrage and improving market efficiency. Also, the event study from the Shenzhen stock connect program indicate that providing better liquidity and avenues to trade stocks improves market efficiency as well. These findings further support previous study such as [Chordia, Roll, and Subrahmanyam \(2008\)](#) which documents that decimalization of US stocks improved market liquidity for stocks and hence market efficiency.

In Chapter Three, we examine the impact of political, economic and trade policy uncertainty on market liquidity. Market liquidity is an essential component of financial markets. [Butler, Grullon, and Weston \(2005\)](#) find that market liquidity is a determinant of cost of raising capital. [Edmans, Fang, and Zur \(2013\)](#) show that there is a positive effect of stock liquidity on governance. Furthermore, [Brogaard, Li, and Xia \(2017\)](#) show that stock liquidity reduces firm bankruptcy risk. Better investor protection leads to lower information asymmetries and narrower spreads and vice-versa ([Brockman and Chung](#)

(2003)).

Uncertainty should increase the adverse selection component of the bid-ask spread and thereby increase transaction costs (Battalio and Schultz (2011)). Another study by Cox and Griffith (2018) shows that political uncertainty arising from the surprise Brexit vote and Donald Trump's election as President of the United States caused a deterioration in liquidity.

Economic policy uncertainty is measured using the Economic Policy Uncertainty Index by Baker, Bloom, and Davis (2016) and trade policy uncertainty is measured by the Trade Policy Uncertainty Index by Davis, Liu, and Sheng (2019). We study political uncertainty that arose due to the Bo political scandal in China during 2012. Using a panel regression and event study regression framework employed by Beber and Pagano (2013). The Panel regressions are employed for regression two widely used monthly average values measures of liquidity- transaction costs and price impact on both the Economic Policy Uncertainty Index monthly values and Trade Policy Uncertainty Index monthly values in two different regressions respectively. Our findings indicate that both types of uncertainties have an adverse impact on both measures of liquidity. Also, the liquidity of smaller firms appears to be more sensitive to economic policy uncertainty index. Whereas, larger firms that are more trade sensitive are more greatly impacted by Trade policy uncertainty. We further note that the liquidity measures of Financial and Real Estate sectors as a whole are more sensitive to economic policy uncertainty. Whereas, the liquidity measures of the manufacturing sector are more sensitive to trade policy uncertainty.

We employ the event study regression technique as employed by Liu, Shu, and Wei (2017) to study the impact of the Bo political scandal on market liquidity. Our findings indicate that the liquidity of SOE firms as measured by our two measures of liquidity are less impacted as compared to non SOE firms. Also, when we consider dual listed A-shares and B-shares, we note that the liquidity of A-shares is impacted more than their B-share counterparts. This is indicative of the fact that institutional investors in B-shares panic less as compared to more emotional retail investors holding A-shares.

We finally study the impact of the US-China trade war on market efficiency using two different measures of market efficiency- the return predictability measure and variance ratio tests. We employ the event study methodology employed by Chang, Luo, and Ren (2014) around the time of the infamous tweet by President Trump in which he commented that trade wars were 'easy' to win and sent markets plunging on March 2, 2018. ²

²The CNBC report is available at: <https://www.cnbc.com/2019/06/29/us-china-trade-talks-at-g-20-timeline-of-how-the-tariff-war-started.html>

We provide a better understanding of the impact of some key challenges being faced by China on its market liquidity, the differential impact of various uncertainties on the liquidity of various sectors of the Chinese economy. Additionally, we exploit the unique features of the Chinese markets such as the existence of SOEs and dual listed shares to further shed light on various aspects of the Chinese markets such as market liquidity and market efficiency which is one of the most dynamic and rapidly growing and transforming markets in the world.

These findings indicate the challenges that the current environment of economic and trade policy uncertainty poses to market liquidity. Policy makers, investors and individuals need to be aware of the potential risks arising from these uncertainties in terms of market liquidity and need to take countervailing actions to avoid the adverse impact of these uncertainties.

Chapter 1

Intraday Momentum Patterns in the Cross Section of Stock Returns

“China is opening up faster than most people believe or think. We do not see any regression of that. If anything, we see a speeding up.”¹

(Henry Fernandez, CEO, Morgan Stanley Capital International.)

“The mainland China stock market is mostly owned by retail investors, so it is very driven by sentiment. Those retail investors are really worried about trade wars, so this foreign investment will help institutionalize the market and slowly make it more dominated by professional investors.”²

(Brendan Ahern, CEO, KraneShares MSCI China A Shares ETF.)

1.1 Introduction

Momentum strategies which are based on buying past winners and selling past losers provide investors with the highest Sharpe ratio of all the strategies that can be potentially employed by investors (Daniel and Moskowitz (2016)). The momentum effect is the effect that occurs when a security’s past return performance persists in to the future. Asness, Moskowitz, and Pedersen (2013) find that the momentum effect is one of the most researched topics pertaining to financial markets and find its prevalence across eight diverse markets and asset classes. Despite its prevalence and persistence, the momentum strategy which generates approximately 12 percent in the U.S. markets is not so prevalent in Asia (Chui, Titman, and Wei (2010)). We wish to conduct a study to further analyze the Heston, Korajczyk, and Sadka (2010) momentum phenomenon which generates extraordinary returns for investors in the US to see if the effect exists in China and can benefit

¹See Bloomberg article <https://www.bloomberg.com/news/articles/2019-02-28/msci-chief-fernandez-says-china-opening-faster-than-some-think>

²See <https://www.cnbc.com/2018/08/31/msci-adds-more-mainland-china-stocks-a-shares-to-its-indexes.html>

the investors. Clearly the returns that can be made from momentum strategies are too significant to be left unexplored for the world's second largest market.

Cooper, Gutierrez Jr, and Hameed (2004) provides an overview of various theories developed to explain the momentum effect and empirically test and provide evidence of the soundness of two of these theories proposed by Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) respectively. There is a slight variation in either theory's explanation of the phenomenon. According to Daniel, Hirshleifer, and Subrahmanyam (1998) there is a positive feedback loop which re-enforces the beliefs of the investors when they see the price of their investments rise. This in-turn re-affirms their initial investment and beliefs and they make further investments in the same set of securities which in-turn leads to further price rises and thereby gives rise to the momentum phenomenon. Whereas, Hong and Stein (1999) offer a slightly different theory. According to Hong and Stein (1999) it takes time for information to spread and while this information disseminates this leads to a momentum effect in prices owing to the fact that more and more people either buy or sell a security as the information reaches them. This in-turn attracts even more investors who are mainly momentum investors (who trade based on past returns) to the security who then further enhance the effect.

There are several studies that suggest that mainly institutional investors are momentum traders. Grinblatt, Titman, and Wermers (1995) study the trading strategies of mutual funds from 1975- 1984 and find that 77 percent of mutual funds were momentum traders. Griffin, Harris, and Topaloglu (2003) find that based on the past day's returns, the top decile of securities is more likely to be bought by institutions who are generally regarded as momentum investors and to be sold by individuals who are traditionally considered to be contrarian investors. Badrinath and Wahal (2002) provide evidence of momentum trading behaviour by empirically examining the trade books of a comprehensive sample of various institutional investors. Furthermore, Choi and Sias (2009) provide evidence of institutional investors herding in to specific industries and exhibiting extreme herding behaviour which supports the formation of the momentum effect.

Bogousslavsky (2016) develop a model which works on the principle of a theory defined as infrequent rebalancing. Infrequent rebalancing is a trading mechanism theory whereby the investors trade systematically and periodically at definite intervals on an intraday or monthly frequency in securities contained in their portfolio. This creates a spiral of trades that leads to autocorrelation and lays the foundation for the phenomenon of momentum (see Bogousslavsky (2016) and references therein). The model borrows heavily from the

theoretical and empirical evidence of earlier studies which document institutional investors as systematically trading periodically at certain times of the day, on certain days of the week and rebalancing particularly at the beginning of the year in January (see [Heston, Korajczyk, and Sadka \(2010\)](#) and references there in).

China is the world's second largest stock market and the largest stock market among emerging markets ([Nartea, Kong, and Wu \(2017\)](#)). However, it is also very different structurally from the US markets. In contrast to the US markets³, the Chinese markets are dominated by individual retail investors with an average age of 50 years and poor education and they exhibit speculative trading (characterized by the highest turn over ratios in the world) and are subject to various regulatory constraints ([Pan, Tang, and Xu \(2015\)](#)). [Kong, Lin, and Liu \(2017\)](#) provide further support to the findings of [Pan, Tang, and Xu \(2015\)](#) and postulate that the unusually high turn over of around 500 percent alludes to the highly speculative or 'gambling' nature of investors in China.

Furthermore, several recent studies have documented the lack of the presence of the momentum phenomenon in China. Some examples of studies which have found lack of evidence for the persistence of momentum in Chinese stocks are [Wu \(2011\)](#) and [Cakici, Chan, and Topyan \(2017\)](#). Moreover, according to [Chen, Hua, and Jiang \(2018\)](#) there is also strong evidence of the presence of a contrarian investment strategy rather than a momentum strategy and this produces abnormal returns for Chinese stock markets. In a contrarian strategy investors short sell best performing stocks and buy the worst performing stocks in the hope that prices will show mean reversion following an extreme run in either direction.

This study is the first study to examine the [Heston, Korajczyk, and Sadka \(2010\)](#) intraday momentum pattern in China and other international markets like the UK and Brazil. Also, this is the first study that examines the momentum strategy in the light of differences in investor composition and trading regulations which act as limits of arbitrage in Chinese markets. The evidence provided in this paper lends support to the argument that the lack of momentum effect in China can be attributed to investor composition and limits of arbitrage.

China's capital markets with the existence of various share classes- A-shares (primarily open to domestic investors), B-shares (primarily for foreign investors) and cross listed H shares (Chinese firms listed in Hong Kong) and trading regulations make it a particularly

³According to [Borochin and Yang \(2017\)](#) institutional ownership in the United States has risen immensely over the past 30 years and in the 2010s, on average every firm had 65 percent institutional ownership

good laboratory to study the impact of regulations on intraday momentum patterns in the cross section of stock returns. These unique ownership and trading regulations are laid out in particular detail by [Chui and Titman \(2017b\)](#) and [Gu, Kang, and Xu \(2018\)](#) who classify them as distinct investor composition and limits of arbitrage respectively.

Many studies are exploiting these features to study various known and unknown phenomena. [Li, Brockman, and Zurbuegg \(2015\)](#) study the incorporation of information in to prices by studying A- shares and H- shares and find that the ability of foreign investors to utilize firm specific information and incorporate it in to prices is one of the implicit benefits of cross-listing. [Gu, Kang, and Xu \(2018\)](#) find that the trading constraints such as price limits and short selling constraints which translate to additional limits of arbitrage have a negative impact on market efficiency. [Chui and Titman \(2017b\)](#) go as far as calling the segmented Chinese market with A and B-shares as an 'ideal laboratory' for studying the varying impacts of investor composition on the momentum effect.

The intraday momentum pattern in the cross section of stock returns that we study is the [Heston, Korajczyk, and Sadka \(2010\)](#) (hereafter [HKS \(2010\)](#)) pattern observed for the US markets. It was the first study to provide empirical evidence on intraday patterns in the cross section of stock returns. The pattern can be interpreted as an intraday momentum phenomenon that leads to significant predictability in daily(24 hour) multiples of each half- hour interval returns, during the trading day; for up to forty trading days in a row. To put it in to perspective, the returns on a stock today between 1:00 to 1:30 pm exhibit momentum over the same interval for up to forty trading days in a row. [HKS \(2010\)](#) identify two potential reasons for this seasonality in return predictability namely - high auto-correlations in institutional fund flows and algorithmic trading.

I intend to answer several unanswered questions not previously examined by researchers. In doing so, I intend to make several important contributions to the existing body of literature. Does the [HKS \(2010\)](#) momentum pattern exhibit itself outside the United States? This question is particularly important as previous studies such as [Heston and Sadka \(2010\)](#) and [Chui, Titman, and Wei \(2010\)](#) have explained that any international evidence on the existence and profitability of a momentum effect serves as a robustness check to the existence of the momentum pattern within the United States as well as providing an opportunity to study the pattern in light of country specific characteristics.

This leads us to the second question - Is there a difference in the propensity of the [HKS \(2010\)](#) intraday momentum pattern with regard to advanced versus emerging markets? [Li, Zhang, and Zheng \(2018\)](#) study the [Heston and Sadka \(2008\)](#) seasonality pattern for 42

advanced and emerging markets from 1995 to 2013 and conclude that return seasonality is economically significant primarily in advanced markets but not in emerging markets. This paves the way for us to explore the existence of another well documented [HKS \(2010\)](#) intraday momentum pattern in the cross section of stock returns to deduce if the pattern exists in both advanced and emerging markets with the same propensity or is there a difference? The answer to this question will enable investors to learn about the potential to profit from an intraday momentum strategy that earns roughly the equivalent of the equity risk premium in the United States([HKS \(2010\)](#)).

We find evidence that [HKS \(2010\)](#) intraday momentum pattern is more prominent in our developed market of UK versus the emerging markets of Brazil and China. Furthermore, our results indicate that the propagation of the pattern is the weakest in the Chinese A-shares market. This prompts us to explore for a potential explanation of the relatively low level of propensity of the pattern in the Chinese A-shares market.

As an initial step in trying to explain the weakness with which the [HKS \(2010\)](#) intraday momentum pattern exhibits itself in the Chinese A-shares market we raise the third question. What is the impact of investor composition on the prevalence of the intraday momentum pattern? [Kaniel, Saar, and Titman \(2008\)](#) find that individual investors have a tendency to take a contrarian strategy as opposed to a momentum strategy typical of institutions and mutual funds ([Grinblatt, Titman, and Wermers \(1995\)](#)) . [Baltzer, Jank, and Smajlbegovic \(2018\)](#) study the entire German stock market and find that foreign investors and financial institutions, particularly the mutual funds are momentum investors whereas, individual investors are contrarians. [Chui, Titman, and Wei \(2010\)](#) study the profitability of some long term momentum strategies across international markets and provide the rationale that such exercises provide a robustness check on results obtained primarily from US data and also provide evidence on how country specific attributes such as culture and institutional differences impact the financial markets.

To study the impact of institutional composition we employ the approach used by [Chui and Titman \(2017b\)](#) which studies the momentum effect using a unique feature of the Chinese markets which is the fact that some of the shares are dual listed as A shares and B shares. The findings of [Chui and Titman \(2017b\)](#) suggest that the momentum effect is prevalent in the B shares owing to investor composition as all other features of the stocks such as voting rights, cash flows etcetera are common between A and B shares.

This study examines the presence of an intraday momentum pattern and it will be interesting to see if investor composition plays a significant role in the presence of our

specific [HKS \(2010\)](#) intraday pattern just as it does according to the findings of [Chui and Titman \(2017b\)](#). My cross sectional regression results as well as high minus low portfolio returns show that the [HKS \(2010\)](#) momentum pattern exhibits itself much more strongly in the Chinese B-shares than their dual listed A-share counterparts. This provides concrete evidence that it is explained partially by investor composition which is the key difference between the two classes of shares.

Another potential explanation for the [HKS \(2010\)](#) pattern’s weakness in China could be the trading regulations. We focus our fourth question specifically on this issue- What is the impact of limits of arbitrage in terms of price limits and day trading constraints on the pattern? According to the price limit rule for Chinese markets, a trader cannot post limit orders to buy or sell a stock that is more than 10 percent higher or lower than the previous close ([Gu, Kang, and Xu \(2018\)](#)). Also, the price limit rule is likely to lead to a low probability of trade execution in the event of a price limit hit ([Gu, Kang, and Xu \(2018\)](#)). Therefore, there will likely be subdued activity in stocks that experience sharp movements in stock prices in either direction. This limitation should deter potential investors who wish to engage in an intraday momentum strategy similar to that of [HKS \(2010\)](#).

[Gao, Han, Li, and Zhou \(2018\)](#) discuss various reasons such as macroeconomic news releases and high volumes of trading activity owing to portfolio adjustments that make the opening and closing half hour intervals particularly important. Our cross sectional regression results also indicate that the [Heston, Korajczyk, and Sadka \(2010\)](#) pattern is mainly concentrated in the first and the last half hour of the trading day for Chinese markets. This is in contrast with the findings of [HKS \(2010\)](#) who document the presence of the pattern through out the day. The findings provide further support to the impact of index inclusion on the Chinese A-shares as mostly indexers are most active during the opening and closing half hour intervals of the trading day ([Gao, Han, Li, and Zhou \(2018\)](#)).

Furthermore, even the most sophisticated investors and analysts regard the Chinese stock market as a “casino” who blame the “erratic and irrational” behaviour on the individual retail investors.⁴ Institutional investors are believed to have various desirable affects on the capital markets. For instance, institutional investors are found to reduce firm misvaluation ([Borochin and Yang \(2017\)](#)), increase innovation output ([Bena, Ferreira, Matos,](#)

⁴This is according to an interview with Jing Ulrich, Vice Chairman for Asia Pacific with JP Morgan Chase Bank. See : <https://www.cnbc.com/2016/01/08/jpmorgan-heres-what-china-needs-to-stabilize.html> and an article published in the Economist which suggests that the Chinese stock market is often referred to as a casino See : <https://www.economist.com/free-exchange/2015/05/26/a-crazy-casino>

and Pires (2017)), improve long-run performance (Appel, Gormley, and Keim (2016)) and lower information asymmetry (Boone and White (2015)) among various others. Furthermore, specifically with regard to the Chinese markets Tian, Wu, and Wu (2018) find that institutional investors provide stability to the market by reducing the impact of extreme swings.

Given the importance of institutional investors, Chinese policy makers and regulators have been steadfast to make the necessary reforms to attract institutional investors. The main reforms can be chronologically summarized as follows- capital mobility restrictions were eased by relaxing rules on Qualified Foreign Institutional Investor (QFII) repatriation (2013), launching of Shanghai connect⁵ (2014), tremendous alleviation of uncertainties regarding the capital gains tax (2014), tightening of rules on stock trading suspensions(2016), Qualified Foreign Institutional Investor (hereafter QFII) and Renminbi Qualified Foreign Institutional Investor (hereafter RQFII) quotas linked to fund size (2016), beneficiary ownership rules made more investor friendly and transparent(2016), Shenzhen connect launched(2016) and an easing of requirements that previously restricted creation of index linked investment products(2017).⁶

In this study, we intend to study the intraday momentum pattern in the cross section of stock returns for the main Chinese share sub-classes namely the A-shares (available under QFII and RQFII quota restrictions to foreign investors), B-shares (available to foreign investors without restrictions) and H-shares(listed in Hong Kong but available to domestic investors through the stock connect program). Our study is related to several other studies that study the momentum effect at relatively longer horizons (see Chui and Titman (2017b), Chui, Titman, and Wei (2010)) in Chinese markets and other markets beyond the United States. However, to our best knowledge this is the first study that looks at intraday momentum in the cross section of stock returns beyond the US market.

To further demonstrate the role of institutional investors in explaining the momentum effect in China we drop the first and last trading intervals of the day. The first and last trading intervals are particularly important for institutional investors who need to re-balance their portfolios based on closing prices, mark to market their holdings, calculate their returns and close overnight risky positions ((Gao, Han, Li, and Zhou, 2018)). We find that the pattern further diminishes when the first and last trading intervals are removed.

⁵Stock connect programs facilitate traders between mainland China and Hong Kong stock exchanges to trade seamlessly using local brokers.

⁶These reforms have been summarized in a report by Ching Ping Chia, MSCI Head of Research for Asia Pacific which is the source of this information . See : <https://www.msci.com/www/blog-posts/the-world-comes-to-china/01002067599>

This shows that the pattern manifests itself primarily owing to institutional investors.

The findings shown in Figure 1.1 (page 28) show that the intraday momentum pattern in the cross section of stock returns is relatively weaker in the all A-shares sample as compared to the UK(chosen due to its size) and Brazil(chosen because it is an emerging market). We attribute these findings to the retail investor dominated markets of China. This study offers a unique opportunity to study the impact of investor composition on the proliferation of the intraday momentum pattern in the cross section of stock returns. Table 1.1 highlights the unique features of China's various share sub-classes. We exploit the dual listed A and B-shares and the cross listed H-shares as these stocks have the same balance sheets and cash flows and only differ in terms of ownership- individual versus foreign/institutional investors. Also, the dual listed A-shares are different from their H-share counterparts since the Hong Kong stock market doesn't constitute the same level of limits of arbitrage in terms of price limits and day trading rules as do the Chinese markets (see Gu, Kang, and Xu (2018)).

Chui and Titman (2017b) go as far as calling the segmented Chinese market with A and B-shares as an 'ideal laboratory' for studying the varying impacts of investor composition on the momentum effect. Figure 1.2 (page 29) and Figure 1.3 (page 30) show the findings for dual listed B-shares and H-shares respectively. These dual listed B- and H- shares show greater strength of the pattern than their A-share counterparts. The difference in the strength of the momentum pattern is even higher for the H-shares and their A-share counterparts because the H-shares provide lower limits of arbitrage which are even more desirable for institutional investors. These findings are consistent with studies in the past such as Kaniel, Saar, and Titman (2008) who find that individual investors have a tendency to take a contrarian strategy as opposed to a momentum strategy typical of institutions and mutual funds (Grinblatt, Titman, and Wermers (1995)). Also, the findings further support the findings of Baltzer, Jank, and Smajlbegovic (2018) who study the entire German stock market and find that foreign investors and financial institutions, particularly the mutual funds are momentum investors whereas, individual investors are contrarians.

The reforms carried out by Chinese policy makers and regulators paved the way for a land mark event. On June 1, 2018 Morgan Stanley Capital International(MSCI hereafter) initiated its first phase of including China's A-shares in to its Emerging Markets Index. This was then followed by the second phase of inclusion on September 1, 2018 of what analysts believe to be a multi-year plan to increase the weight of A-shares by MSCI in its Emerging Markets Index. The index is followed by active and passive managers controlling

assets worth 1.6 trillion US Dollars and some analysts are forecasting a net inflow of upto 600 billion US Dollars in to the Chinese A-shares over the next five to ten years after one hundred percent inclusion is achieved.⁷

While these reforms have lead to the partial inclusion of A-shares in the Emerging Markets Index by MSCI, there are investors who are optimistic and some that are sceptic of the impact of partial inclusion of A-shares in to the MSCI Emerging Markets Index and will not be influenced by it in terms of their stock picking.⁸ We shed more light on the impact of index inclusion on the 232 A-shares and show that institutional ownership, percentage of float held by institutions, number of institutions holding the stocks and foreign ownership all four measures show an increase post inclusion. The changes in key variables of institutional ownership are shown in Table 1.11. Institutional holdings rise from 49 percent before inclusion to 55 percent after inclusion. The percentage of float held by institutions rises from 18 percent to 29 percent. The institutional base in terms of the number of institutions owning or trading the stocks has risen to 150 from a pre-inclusion level of 100. Also, domestic ownership declined by 2 percent and made way for an increase in foreign ownership.

We use the exogenous increase in institutional ownership as a result of index inclusion of 232 A-shares to further study its impact on the intraday momentum pattern in the cross section of stock returns. The results of the impact of inclusion in the index are depicted in Figure 1.4 (page 31). We observe that following the inclusion in the MSCI Emerging Markets Index, the 232 A-shares exhibit the intraday momentum with greater strength and point to the importance of institutional investors in explaining the intraday momentum in the cross section of stock returns. This provides further evidence as to the impact of institutionalization on prevalence of the pattern and also further re-enforces our initial findings which differ between all A-shares and the UK and China as well as between A-shares and their dual listed B-share and cross listed H-share counterparts. These findings are consistent with Nofsinger and Sias (1999) who show that herding and feed back trading by institutional investors is more effective in leading to the momentum effect as compared to that by individual investors.

⁷The 600 billion USD figure has been estimated by Steven Sun, head of research at HSBC Qianhai, a Shenzhen-based securities company. This article can be found at <https://www.ft.com/content/3ea51148-632f-11e8-a39d-4df188287fff>

⁸Nicholas Yeo from Aberdeen Standard Investments sees no immediate effect of the inclusion on his investment picks. Eric Brian of JP Morgan Asset Management views the move as largely symbolic and sees no impact on the firm's approach to stock picking and portfolio selection. See : <https://www.bloomberg.com/news/articles/2019-03-01/msci-s-latest-china-call-positive-but-mostly-symbolic-analysts>

Li and Wang (2010) show that institutional investors in China have a tendency to mostly pick large stocks and concentrate their daily trades in them. We now turn our focus to the impact of size on the propensity with which the intraday momentum pattern propagates. Figure 1.5 (page 32) shows the dispersion of the intraday momentum pattern across small, medium and large stocks. We classify the all A-shares sample in to small, medium and large stocks based on size terciles. Our regression results indicate that the pattern is strongest in large stocks and weakest in small stocks. This confirms findings of Li and Wang (2010) and also further re-enforces the fact that the pattern is weaker in Chinese A-shares due to a lower level of institutional holdings and more active participation by retail investors. Furthermore, Campbell, Ramadorai, and Schwartz (2009) lend support to our findings of relatively weaker presence of the intraday momentum pattern in our study as they point to the highly persistent trading behaviour of institutions in daily trading which is a pre-requisite for the intraday momentum effect as modelled by (Bogousslavsky, 2016) that we are studying.

This study goes further beyond just examining the existence of the HKS (2010) pattern in the Chinese stock market. We now turn to half hour trading intervals which are not exact half hour multiples of a trading day, but are actually within the trading day and extend this to all intervals for up to three trading days and study the markets for any patterns that may arise therein and that may shed more light on the Chinese retail investor's trading preferences. Our findings indicate the presence of a strong reversal pattern during the first three half hour intervals immediately after the passing of a 24 hour period or a whole trading day for up to two days in a row. These findings re-enforce the contrarian nature of retail investors that has been previously documented in the literature (Kaniel, Saar, and Titman (2008)). It shows that retail investors place contrarian trades that are predictable and their holding periods are just over 24-hours and point to the day trading rule as playing a role in their behaviour. This is not the case for UK markets which demonstrate no such reversals just beyond the daily trading lag.

In addition, when we run the regression for half hour returns on intraday lags within the trading day, we notice that short term return reversals last for 0 to 30 minutes for Chinese markets and they last for 0 to 30 minutes for the UK market as well. However, the regression estimate and t-statistics are higher for the Chinese markets. This shows that Chinese markets as a whole are somewhat less efficient than UK markets. These findings are consistent with Chordia, Roll, and Subrahmanyam (2005) who find that it takes between 30 to 60 minutes for the US markets to become efficient but their sample

period ends in 2002.

The remainder of this paper is organized as follows. Section 2 discusses the data and methodology. Section 3 provides the empirical findings and the discussion. Finally, Section 4 offers a conclusion to the paper.

1.2 Data and Methodology

1.2.1 Data description

Two distinct databases have been used to collect all the data required. The high frequency intraday trading data is collected from Bloomberg. We use Bloomberg to collect data for China, the UK and Brazil in order to compare the Chinese market results with a well-developed UK market and another developing BRIC country, the Brazilian market. The appropriate Bloomberg data collection screening filter is used to screen out common stocks that are traded in the domestic currency and are domiciled within the country. The exception to this rule is the collection of data for B-shares which are traded in US Dollars and Hong Kong Dollars and not in the domestic currency. Also, for the Chinese dual listed H-shares we consider the shares even though they are traded outside mainland China on the Hong Kong stock exchange.

For China, this data is then classified as A-shares, B-shares or dual listed in Hong Kong as H-shares and as B-shares in either Shanghai or Shenzhen. This is done through the firm classification data collected from The China Stock Market and Accounting Research database (CSMAR). CSMAR is widely used by researchers and there are no reports of discrepancies in share classifications i.e. A, B or dual listed in Hong Kong and China and also no classification errors are known to date. The final sample contains all firms for which the data can be matched from CSMAR and to further avoid inclusion of exchange traded funds, preference shares, bonds etcetera we manually check and verify the International Securities Identification Number (ISIN) of each and every security to ensure only equity listings are included in the dataset.

For the purpose of studying intraday patterns in the cross section of stock returns, following the methodology of [Heston and Sadka \(2010\)](#) all firms that can be matched on both Bloomberg and CSMAR are considered. We follow [Fong, Holden, and Trzcinka \(2017\)](#)'s methodology to apply specific filters to match trades with quotes and leave out potentially spurious observations such as those with negative spreads (where bids are higher than asks), zero or negative volume and those conducted outside regular market trading

hours. This will ensure that our results are not driven by spurious observations. Also, the data from Bloomberg is considered to have a high correlation with the Thomson Reuters Tick History (TRTH) database. The correlation is known to be as high as 99.19% (Fong, Holden, and Trzcinka (2017)). This should alleviate any concerns about the accuracy of data obtained from Bloomberg.

Our primary sample period for all Chinese, UK and Brazilian stocks starts on June 1, 2016 and ends on March 1, 2019. The sample period is divided in to two periods before June 1, 2018 and after June 1, 2018 for the 232 A-shares that were included in the Morgan Stanley Capital International (MSCI) index for Emerging markets beginning from 1st June, 2018. This is done to study the impact of index inclusion on the intraday pattern exhibited by the included stocks.

We begin by providing summary statistics of the sample of stocks that we consider for the UK, Brazil and China. For China the sample is sub-divided in to three parts A-shares only, dual listed A-shares and B-shares and dual listed A-shares and H-shares in Table 1.1. The total number of firms considered for the UK and Brazil are 1457 and 365 respectively. For China, the number of A firms in our sample is 3473. The number of dual listed A and B-shares is 84 and the number of dual listed A and H-shares is 87. Table 1.2 also provides summary statistics of half hour returns for the sample.

1.2.2 Description of Variables

1. R : These returns are calculated using the last trading price at the end of each half hour interval less the opening price at the beginning of the interval divided by the opening price as calculated by HKS (2010).

2. MPR (Midpoint Returns): These returns are calculated for the interval t using the average of the bid-ask prices at the end of interval $t-1$ and the average of the bid-ask prices at the end of interval t . The difference between the two is divided by the average of the bid-ask prices at the end of interval $t-1$ to obtain the midpoint returns.

1.2.3 Methodology

Our aim in this study is to examine the existence of an intraday pattern in Chinese Markets as observed by HKS (2010) and modelled by Bogousslavsky (2016). These two studies examine and model a continuation pattern in the cross section of stock returns at 24-hour multiples for each trading interval between 8:00 am to 4:30 pm on the NYSE considering a sample of all NYSE firms. The pattern is studied using the cross sectional

regression approach following the footsteps of [Jegadeesh \(1990\)](#) and further checking the statistical significance of the estimates by incorporating [Fama and MacBeth \(1973\)](#) t-statistics.

While the cross sectional regression approach is the first step in examining the existence of the return continuation pattern at integer multiples of the trading day for each half hour interval, a second method is employed by [HKS \(2010\)](#) to study the economic significance of the pattern in line with [Jegadeesh and Titman \(1993\)](#). They sort the portfolios in to top(best) and bottom(worst) performing deciles sorted every half hour. These top and bottom decile are then composed in to a portfolio where the top decile stocks are bought and bottom decile stocks are shorted during the same half hour interval for the next forty days. The net return on the strategy turns out to be economically and statistically significant for the next forty days as shown by [HKS \(2010\)](#). They show that on the first day the strategy earns a mean return of 3.01 basis points which is enough to offset the equity premium. In our study, we employ the same techniques as employed by [HKS \(2010\)](#). We sort the stocks based on their half hour returns in to top and bottom deciles with an equal number of stocks in each decile. These stocks are then held on to for the next forty days during the corresponding 24 hour multiple of the interval in question. The trading day is slightly shorter in the Chinese markets and we end up with 8 half hour intervals from 9:30 to 11:30 am and then 1:00 pm to 3:00 pm post lunch break.

$$MPR_{i,t} = \alpha_{k,t} + \beta_{k,t}MPR_{i,t-k} + \epsilon_{i,t} \quad (1.1)$$

Where t is the collection of all half-hour intervals for which the stock trades during the sample period, in case of China this going to be 8 half hour intervals from 9:30-11:30 am and from 1:00 to 3:00 pm respectively. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. k is multiple of 8 (which makes it a lag equivalent to a whole trading day), it assumes values of 8, 16, 24, 32, 40, ..., 312 and 320 for a daily lag of 1, 2, 3, 4, ..., 39 and 40 days.

We first estimate mid-point returns based on the average of bid-ask prices for each half hour interval of the trading day for each market. We don't use trade price returns to avoid any potential bid-ask bounce effects. Most recently [Hasbrouck \(2018\)](#) has highlighted that for intervals of up to 1 hour, the trade price change may simply be the artefact of the bid-ask bounce and also there is an issue with calculating the returns since the trades may not necessarily be at precisely the beginning and ending of a half hour interval. Also, as pointed out by [HKS \(2010\)](#), short term return reversals that they find at lags less than 1

trading day are merely due to the bid-ask bounce. Since we intend to study short term return reversals as well, it is prudent that we choose mid-point returns to rule out the influence of the bid-ask bounce in our findings.

We then run cross-sectional regressions of these half-hour interval returns on lagged half-hour returns during the same daily interval for up to 40 days. The coefficients are then averaged over time as per the [Fama and MacBeth \(1973\)](#) approach. We further split the Chinese stocks in to Chinese A- shares, dual listed A- shares and their B-share counterparts and Chinese A-shares and their dual listed H-share counterparts. The Chinese A-shares are open for investment to only domestic investors, the B-shares are open to both domestic and foreign investors and the H-shares are listed in Hong Kong. This segmentation leads to significant difference in investor composition. The Chinese A-shares are characterized by retail investor ownership ([Nartea, Kong, and Wu \(2017\)](#)). Whereas, the B-shares are primarily held by foreign investors ([Chui and Titman \(2017b\)](#)). The main advantage is that there are some shares that are dual listed as A and B- shares. A summary of the salient features of all share classes of interest in the Chinese markets is provided in [Table 1.1](#).

We perform the regression analyses explained above on both A-shares and their B-share counterparts. Segregating the sample in to dual listed A and B-shares provides an insight in to the role of investor composition in explaining the intraday momentum pattern of [HKS \(2010\)](#). We now turn to segregating the sample in to dual listed A and H-share counterparts. This provides an avenue to study the impact of limits of arbitrage on the intraday momentum pattern. We run cross-sectional regressions of current 30 minute interval returns on returns during the same interval on previous days for up to 40 days and then average the coefficients over time as per the [Fama and MacBeth \(1973\)](#) approach. The results indicate that the intraday momentum is much stronger in the H-shares as compared to their A-share counterparts. This difference can be attributed to low limits of arbitrage in the Hong Kong stock markets. They are not subject to limits of arbitrage such as price limits and the day trading rule as is applicable to the Chinese markets.

Initially, we consider all A-shares listed in Chinese Markets. We then segregate our sample in to dual listed A-shares and dual listed B-shares following [Chui and Titman \(2017b\)](#). [Chui and Titman \(2017b\)](#) find that the absence of momentum in the A-shares is due to difference in investor composition as dual-listed B-shares with nearly the same features exhibit momentum in returns much more profoundly than their A-share counter-

parts. This motivates us to exploit this unique feature of the Chinese markets to study the differential impact of investor composition on intraday momentum. Furthermore, we split the sample in to cross listed A-shares versus their H-listed counterparts. We find that the intraday momentum pattern is far more profound in the H-shares market than in the corresponding A-shares market. We can hence infer that investor composition as well as market regulations can play a major role in explaining the differences in intraday momentum patterns as exhibited by these ‘twin’ shares.

To investigate the impact of limits of arbitrage on the Chinese A-shares, we conduct yet some more tests. We drop the stocks that traded in the top and bottom deciles for each half hour interval that are considered. This ensures that any stocks that hit the price limit whether upper or lower or are likely to hit the higher or lower price limit are excluded. When these stocks are removed, the strength of the intraday pattern in the Chinese A-shares rises considerably based on the regression coefficients for the regression discussed above in detail.

Our analyses also involves analysing the intraday momentum pattern among the Chinese A-shares market based on cross sectional differences in stocks. The entire sample is split in to large, medium and small stocks based on market capitalisation. There is no significant difference in the pattern in terms of the regression coefficients obtained and size doesn’t explain the pattern. Furthermore, motivated by the recent study [Gao, Han, Li, and Zhou \(2018\)](#) who state that the first half hour and last half hour of trading are particularly important we run another regressions as in [HKS \(2010\)](#) to check the concentration of the pattern in the first and last half hours where the first and last half hour intervals are dropped. The reason cited by [Gao, Han, Li, and Zhou \(2018\)](#) for the significance of the first and last hour of trading are that- important announcements are typically made during the first half hour of trading and institutional investors, mutual funds etcetera rebalance their portfolios during the last half hour prior to market close.

To further determine the economic significance and statistical significance of this pattern for China, UK and Brazil we now turn to intraday momentum portfolio analyses as conducted by [HKS \(2010\)](#). The performance for the portfolios formed on the basis of each half-hour interval’s returns is tested. The stocks are sorted every half hour and portfolios are formed using the top and bottom deciles and their half hour returns are observed for the next forty days(during the same half hour interval). The average return spreads(top minus bottom decile) on portfolios formed on the basis of the performance during the relevant historical half hour (with lags 1 to 40 days) interval are reported. The stocks are

grouped in to ten portfolios with an equal number of stocks in each portfolio.

We use alternative measures of returns such as trade, bid to bid and ask to ask returns as used by [HKS \(2010\)](#) and find that at the daily lag level, it doesn't affect our results. The only difference is that for lags close to $k=1$, the negative coefficients are observed beyond one lag. This is in line with the findings of [HKS \(2010\)](#) who cite the bid-ask bounce as the reason for finding negative coefficients using trade returns. Moreover, we use intervals of 5 minutes to 60 minutes to see if a similar intraday pattern is prevalent for any of these intervals and we find no evidence to believe that any other pattern of return continuation beyond the half hour interval exist. This alleviates concerns that our findings may be driven by other effects that we may not have considered.

1.3 Empirical results

1.3.1 Intraday Return Predictability Based on Previous Day's Return in the Same Half Hour Interval

Our initial sample contains 3,473 A-shares listed on the Chinese stock exchanges from June 1, 2016 to March 1, 2019. We report the regression results for the regression of each trading interval from 9:30 to 11:30 am and from 1:00 to 3:00 pm (which makes a total of 8 daily trading intervals) on their lagged returns for lags of 8,16, 24,32,...,312 and 320 which corresponds to daily lags of 1,2,3,4,..., 39 and 40. Like [HKS \(2010\)](#) we employ the cross sectional regression approach applied by [Jegadeesh \(1990\)](#) and report the corresponding [Fama and MacBeth \(1973\)](#) t-statistics. The results are reported in Table 1.3.

We observe that in general, the pattern is less profound in terms of both the estimates and the t-statistics for the Chinese A-shares. To provide a sense of the magnitude of this difference, the pattern as reported for a daily lag of 1 day is most profound for the U.S. market as reported by [HKS \(2010\)](#) in their Table I, the estimate has a co-efficient of 1.19 and a t-statistic of 18.22. Whereas, our estimate for a daily lag of 1 day has an estimate with a co-efficient of 0.36(raw), 0.18 (standardized) and a t-statistic of 2.94. This is a very striking contrast as when we look and compare the estimates for other lags up to forty days, we observe that for the U.S. markets the highest report estimate and t-statistic is that for the daily lag of 1 day. However, for the Chinese market it appears that the lowest estimate and corresponding t-statistic is that for the lag of 1 day. The estimates for greater lags are somewhat comparable in terms of statistical significance i.e. the t-statistics, but

relatively weaker in terms of economic significance i.e. the actual regression coefficients.

To add to the validity of our analyses and to provide a robustness check, we also include the UK market (which is a large market outside the US like China) and Brazil (which is another emerging market like China). As can be seen in Table 1.3, the regression coefficients and relevant t-statistics showing the results for China are visibly smaller than that of UK and Brazil which are 1.82(raw), 0.81(standardized) and 1.12(raw), 0.60(standardized) with t-statistics of 10.18 and 7.22 respectively for a lag of one trading day for UK (Brazil) respectively.

This finding can be simply interpreted as a very weak intraday momentum effect for a daily lag of 1 day. However, contrary to U.S., UK and Brazilian markets where the effect is most profound for a daily lag of 1-day, it is the weakest for China. As the effect tapers off with increasing lags of up to forty days, the effect in China seems to be more stable beyond the first day. Unlike the US, UK and Brazil we see a peaking out of this effect on the third trading day. This motivates us to study the factors that are essentially curtailing this effect for a daily lag of 1-day.

This finding contributes to the evidence provided by earlier studies such as Chui and Titman (2017b) which find a weaker prevalence of the momentum effect in Chinese A-shares. Also, Li, Zhang, and Zheng (2018) study the Heston and Sadka (2008) seasonality pattern for 42 advanced and emerging markets from 1995 to 2013 and conclude that return seasonality is economically significant primarily in advanced markets but not in emerging markets. Furthermore, Chui, Titman, and Wei (2010) study the profitability of some long term momentum strategies across international markets and provide evidence they generally under perform in Asian markets owing to cultural differences in terms of the level of individualism.

1.3.2 The Existence of Intraday Momentum in A-Shares versus B-Shares

The Chinese market offers a very unique opportunity to study the impact of investor composition as explained in detail by Chui and Titman (2017b). Chui and Titman (2017b) argue that the dual listed stocks which have both A and B-shares trading in the market have essentially the same type of features in terms of voting rights and cash flow rights but differ in investor composition. The Chinese A-shares are owned by domestic investors the majority of whom are retail investors versus B-shares that are held mostly by foreign investors who are mainly sophisticated institutional investors.

We only consider the sample of A-shares which have a corresponding listing of B-share and are dual listed. We end up with a sample of 84 dual listed A and B shares. The results for the cross sectional regressions to examine the intraday pattern observed by [HKS \(2010\)](#) are reported in Table 1.4. We observe that the regression co-efficient for the dual listed A-shares is somewhat better than the aggregate A-share sample. The estimate has a co-efficient of 0.55(raw), 0.26(standardized) and a t-statistic of 2.85 for a daily lag of 1 day. Whereas, our dual listed B-share sample has an estimate with a co-efficient of 1.30(raw), 0.67(standardized) and a corresponding t-statistic of 6.32. While both these estimates for the A-shares and B-shares have estimates that are statistically much less significant than the U.S. estimate which had a t-statistic of 18.22 for the first daily lag, it is evident that B-shares clearly demonstrate a higher alignment with the U.S. markets in terms of exhibiting this pattern.

Interestingly, [Chui and Titman \(2017b\)](#) also find that the momentum effect for longer horizons is more prevalent in B-shares as compared to A-shares. They use this evidence to arrive at the conclusion that since the only significant difference between dual listed A-shares and B-shares is investor composition, it is plausible to say that it is the difference in investor composition that determines the existence of the momentum effect. Our findings, support and complement their findings by providing evidence that even very short term momentum effect at the intraday level is much stronger in the B-shares as compared to A-shares and provides further support for the argument that it is indeed investor composition that explains why the momentum effect is not very strong in China as observed by [Chui, Titman, and Wei \(2010\)](#). [Nofsinger and Sias \(1999\)](#) further support our findings they show that herding and feed back trading by institutional investors is more effective in leading to the momentum effect as compared to that by individual investors. Our findings are also consistent with [Akbas, Armstrong, Sorescu, and Subrahmanyam \(2015\)](#) who show that mutual funds have a tendency to invest in past holdings that were winners and liquidating past losers, thereby exacerbating the momentum effect itself.

1.3.3 The Existence of Intraday Momentum in H-Shares versus cross listed A-Shares

We now turn our attention to cross listed A-shares and H-shares. In addition to the difference in investor composition as discussed in section 3.3, the A-shares and H-shares differ in the fact that Hong Kong is a developed market and has negligible trading constraints as compared to China where there are price limits, short selling constraints

and day trading constraints (see [Gu, Kang, and Xu \(2018\)](#); [Chui and Titman \(2017b\)](#)). We have 87 firms in our sample that are dual listed with both A-share listings and H-share listings.

We conduct the same regression analysis based on [HKS \(2010\)](#) as described in earlier sections. The results for the dual listed A-shares and their cross listed H-share counterparts are reported in Table 1.5. The comparison sheds light on a very substantial difference in the existence of the intraday momentum pattern documented by [HKS \(2010\)](#) and modelled by [Bogousslavsky \(2016\)](#) for U.S. markets among the A-shares and their cross listed H-share counterparts.

The pattern appears to be quite subdued for the A-shares with the estimates for the co-efficient and t-statistics corresponding to a daily lag of 1 day being most weak relative to those of the H-shares at 0.50(raw), 0.26(standardized) and 2.69 respectively. Then on, the pattern seems to manifest itself more strongly and is statistically significant for up to twenty days. This is in sharp contrast to the manifestation of the pattern both in terms of the estimates for the co-efficient and the corresponding t-statistics for the cross listed H-shares in the Hong Kong market which are the highest for a daily lag of 1 day with a regression estimate of 4.02(raw), 0.85(standardized) and a t-statistic of 10.45 respectively. For the H-shares, the effect seems to decay from the first day as we move towards a lag of 40 days. However, the pattern is still significant for forty days with the last t-statistic being higher than 3 for all but one day.

This evidence is the first intraday evidence from outside the United States that documents the existence of the pattern discovered in [HKS \(2010\)](#). It also sheds light on the fact that while investor composition explains the momentum effect in part, as demonstrated by a stronger presence of the pattern in dual listed B-shares as compared to their A-share counterparts, the difference is even more substantial if the trading constraints are removed as in cross listed H-shares. This provides further motivation to study the impact of trading constraints on the intraday momentum effect.

1.3.4 Controlling for Size

[Li and Wang \(2010\)](#) show that institutional investors in Chinese markets have the tendency to herd in large stocks. There may be various reasons for this phenomenon. Previous studies have regarded large stocks as being more price efficient and liquid ([Chordia, Roll, and Subrahmanyam \(2005\)](#)). Also, owing to the need to be able to liquidate securities urgently in the event of poor performance, specifically open ended funds have

to be sure that they will be able to liquidate the securities at any cost (Coval and Stafford (2007)). This is easier if an institution invests in large and generally more liquid stocks in an emerging market.

We now therefore, conduct our analysis to examine the existence of the intraday pattern in the Chinese Markets by segregating our sample in to small, medium and large firms by size (market capitalization) terciles. The results are reported in Table 1.6. We find that the pattern manifests itself more strongly as we move from small to medium and from medium to large firms.

The weakest estimate for the lag of 1 day comes from the small firms, 0.28(raw), 0.12(standardized) with a t-statistic of 2.82 and then there is a monotonous rise to 0.33(raw), 0.17(standardized) with a t-statistic of 2.96 for the medium firms and the strongest estimate for a daily lag is shown by large firms with an estimate of 0.46(raw), 0.28(standardized) and a t-statistic of 3.05. We do notice however that across small, medium and large firms alike, the momentum pattern is strongest for the lag of 3 days. This is also true for the all A-share sample discussed in Section 3.1 and presented in Table 1.3.

The results clearly indicate that larger firms exhibit momentum to a greater extent and point to the fact that institutional investors who herd mostly in larger stocks have a big role in driving this phenomenon in Chinese stocks.

1.3.5 Controlling for Time of Day

Gao, Han, Li, and Zhou (2018) find evidence of the existence of an intraday momentum pattern where the first half hour returns on the S&P ETF predict the last half hour of returns. In addition to the S&P ETF, Gao, Han, Li, and Zhou (2018) find similar evidence of the existence of an intraday momentum pattern in ten other domestic and international ETFs that are actively traded. Bogousslavsky (2016) cite some anecdotal evidence that some investors are only active at the beginning and the end of the day. However, they find that their pattern is not limited to the opening and ending half hour intervals. To examine this further, we exclude the first and last half hour from our sample and conduct the regression analysis once again to see if it makes any difference. The results from this analysis are reported in Table 1.7. Our regression is the same as done in previous sections following HKS (2010). Also, institutional investors have particular interest in closing prices as they need to re-balance their portfolios, mark to market their holdings and calculate returns based on them (see Gao, Han, Li, and Zhou (2018) and references therein). This further proves that when the opening and closing intervals are excluded from the sample,

we are further excluding the activity of institutional investors and thereby minimizing the presence of the momentum effect.

We find that none out of the forty regression estimates have a t-statistic that is greater than 3. The effect is almost non existing as demonstrated by the weakness of the estimates(both raw and standardized) and their corresponding t-statistics. This provides some evidence that the existence of the effect is strongly dependent on the time of the day for the Chinese A-share market. To further clarify the findings in simple words, we can say that the first half hour interval and last half hour interval exhibit the bulk of the intraday momentum for the Chinese A-share markets and the effect is not consistent [HKS \(2010\)](#) who find the pattern as being prevalent across all half hour intervals of the trading day and not just the first and last half hour. Our findings are more consistent with [Khademalomoom and Narayan \(2019\)](#) who study the intraday patterns in currency markets and find the existence of a time of the day effect.

1.3.6 Controlling for Price Limits

This section provides perhaps the most compelling evidence that the effect documented by [HKS \(2010\)](#) is not observed in China and the presence of the intraday momentum pattern is weakest for the daily lag of 1 day. Whereas, in the U.S. it is strongest for a daily lag of 1 day. To simply put it, it is found in the U.S. that the returns for instance between 10:00 and 10:30 today for a particular stock will predict its returns for the same interval tomorrow. However, in China it is seen that this predictability is the lowest between today and the next day. We explore major reasons for it and the existence of price limits is a good candidate to explain this effect as stocks that are affected by price limits experience significant trading frictions and the likelihood of execution of trades over the subsequent days also becomes low ([Gu, Kang, and Xu \(2018\)](#)).

We do this by dropping out the top and bottom decile from our sample for every half hour interval reported in our sample. This is done to avoid the market frictions that traders face in the existence of price limits as explained in [Gu, Kang, and Xu \(2018\)](#) where the likelihood of trade execution falls as the stock hits its price limits. As the top and bottom decile for each half hour exhibit the extremes in terms of price movements, it is plausible to remove them from our analyses and determine whether it is the daily price limits which curtail the intraday momentum pattern in Chinese markets.

To filter out the effect of price limits, we adapt an innovative approach which is to sort the stocks into deciles every half hour and remove the top and bottom decile from the

sample and conduct the similar regression analysis that we have conducted thus far based on [HKS \(2010\)](#). The results from the analysis are reported in Table 1.8.

The results highlight the impact of price limits which are mostly likely to affect top and bottom decile of stocks sorted on returns at the end of each half hour interval. We notice that the regression estimates(both raw and standardized) for the daily lag of 1 day are much better in this sample with a co-efficient of 0.52(raw), 0.27 (standardized) and a t-statistic of 4.92 versus a co-efficient of 0.36(raw), 0.18(standardized) and a t-statistic of 2.94 for the wider all A-share sample which doesn't drop the top and bottom decile stocks. This provides evidence that price limits hamper the intraday momentum effect that is the subject of our analysis in this study.

1.3.7 Day Trading Rule, Return Reversals and Contrarian Strategies

[HKS \(2010\)](#) document that short-term return reversals last for 30-60 minutes in the U.S. markets. We document similar results for the UK where return reversals last for up to thirty minutes. However, cross sectional regression results indicate that for China return reversals last for 30-60 minutes. This indicates that it takes longer for Chinese stocks to converge to market efficiency. Also, the resolving of return reversals within 30 minutes by the UK market as a whole indicates that markets have become more efficient since 2005 when [HKS \(2010\)](#) period of study ends.

In Table 1.9 we report the cross-sectional regression results for the regression of each trading interval from 9:30 to 11:30 am and from 1:00 to 3:00 pm (which makes a total of 8 daily trading intervals) on their lagged returns for lags of 1,2,3,...20 for China and 1,2,3,...51 for the UK since they have 17 half hour intervals as they trade from 8:00 am to 4:30pm . Like [HKS \(2010\)](#) we employ the cross sectional regression approach applied by [Jegadeesh \(1990\)](#) and report the corresponding [Fama and MacBeth \(1973\)](#) t-statistics.

The most striking feature is the return reversibility in China at intervals just beyond the 1 day lag. This suggests that due to the ban on day trading, a lot of traders rush to unwind their positions and potentially book profits on trades from the previous day as suggested by the negative sign of the co-efficient and this effect is highly significant. Also, it can be interpreted as investors taking a contrarian strategy. This eventually has implications for market efficiency as the ban on day trading leads to aggressive behaviour to reverse positions as soon as the 24 hour period passes. The evidence is supportive of the findings of [Kaniel, Saar, and Titman \(2008\)](#) and [Baltzer, Jank, and Smajlbegovic \(2018\)](#)

who find that domestic individual investors are most likely to be contrarians and engage in contrarian strategies rather than momentum strategies. Our findings are consistent with [Li, Zhang, Feng, and An \(2019\)](#) who find that the day trading rule or ‘T+1’ settlement rule which restricts intraday buying and then selling in Chinese markets is also responsible for the weaker presence of herding phenomenon on the sell side as compared to the buy side.

1.3.8 Intraday Momentum Portfolio Returns

Following the methodology of [HKS \(2010\)](#) who follow the portfolio formation of [Jegadeesh and Titman \(1993\)](#) we also conduct a similar analysis. Table 1.10 reports the performance for the portfolios formed on the basis of each half-hour interval’s returns. The stocks are sorted every half hour and portfolios are formed using the top and bottom deciles and their half hour returns are observed for the next forty days (during the same half hour interval). We ensure that all deciles have the same number of stocks as required by [HKS \(2010\)](#) as it is critical to form equal weighted portfolios. All intervals from 8:00 to 16:30 are taken and stocks are sorted every half-hour for the UK markets. The sample includes all UK firms from 1st January, 2017 to 31st December, 2017. For the Chinese A-share markets all intervals from 9:30 to 11:30 and then 1:00 to 3:00 pm are taken. The average return spreads (top minus bottom decile) on portfolios formed on the basis on the performance during the relevant historical half hour (with lags 1 to 40 days) interval are reported. The stocks are grouped in to ten portfolios with an equal number of stocks in each portfolio. The returns are reported in basis points to make more economic sense.

We find that the pattern is quite strong in the UK markets and for a daily lag of 1 day, the portfolio returns are nearly 4 basis points, which is higher than what has been reported for the US and the t-statistics are highly significant with a value of 13.85. This evidence is the first intraday evidence of the pattern documented by [HKS \(2010\)](#) outside the US in terms of an equally weighted portfolio return. This is a striking finding since usually it is seen that post publication return predictability of variables declines ([McLean and Pontiff \(2016\)](#)). We observe that for the UK, the effect yields significant and positive returns specially during the first ten days.

For Chinese A-shares, the picture is rather different. We observe that the spreads are much narrower and the effect is not significant particularly for the strategy based on 1 daily lag and the lags beyond 10 days. The high minus low portfolio return on a strategy based on a 1 day lag for Chinese A-shares is 0.55 basis points and has a t-statistic of 1.52.

We find that the intraday momentum pattern is strongest for the strategy based on the high minus low portfolio returns with a lag of 3 days.

The Brazilian markets and the dual listed B and H-shares are much like the UK and US. We see a peaking of the intraday momentum pattern in terms of returns when we use a 1 day lag strategy to form a portfolio based on high minus low stocks. The profits are of the range of 2.36 basis points for B-shares, 3.54 basis points for H-shares and 3.09 basis points for Brazil for a portfolio formed based on a 1 day lag. These markets are dominated by institutional investors and the intraday predictability in the cross section of stock returns seems synonymous with them. Whereas, in the retail dominated market of Chinese A-shares, the pattern is weakest for a 1 day lag. The day trading rule, the price limit rule and retail investor procrastination serve to explain the different set of findings for the Chinese A-shares.

1.3.9 Inclusion of A-Shares in the MSCI Emerging Markets Index

We now consider the 232 A-shares that were included in the Morgan Stanley Capital International (MSCI) Emerging Markets Index from June 1, 2018. It is believed that the inclusion of these Chinese A shares in the MSCI index has significantly increased the attractiveness of these shares as well as the Chinese stock market as a whole to international investors and thus their liquidity. Indeed Table 1.11 shows that since the inclusion, these shares have had a substantial increase in institutional owners.

We study these stocks from April, 2016 to May 31, 2018 (before inclusion in the index) and from June 1, 2018 to March 1, 2019 (after inclusion in the index). In Table 1.12, we report the regression comparison before and after the inclusion in the MSCI index. We notice that the cross sectional regression estimates experience a significant increase after the inclusion in the MSCI Emerging Markets Index. Also, the statistical significance experiences an increase across the board ranging from 1 to 40 days post inclusion. Of particular interest is the fact that post inclusion, the 1 day lag co-efficient(both raw and standardized) estimate is the biggest economically and most significant statistically. This further signals behaviour similar to the US and UK. Therefore, it leads us to conclude that inclusion has lead to a shift in behaviour of these stocks that now behave more in line with stocks that have a greater institutional base of investors.

Furthermore, as a robustness check to our regression estimates, as in Table 1.10, we construct a high minus low portfolio in which we go long on the top decile stocks and

short the bottom decile stocks based on each half hour’s return performance during the day and hold it until the same interval the following trading day (for up to 40 days). The results are reported in Table 1.13. The average return spreads (top minus bottom decile) on portfolios formed on the basis of the performance during the relevant historical half hour (with lags 1 to 40 days) interval are reported. The high minus low portfolio returns experience a significant increase in the amount of returns generated. For instance, for a strategy that considers a lag of 1 day the returns before inclusion in the index were 1.44 basis points, whereas, after the inclusion these returns rise to 2.85 basis points.

1.4 Conclusion

This study is the first to provide empirical evidence on the existence of the intraday pattern documented in the literature by [HKS \(2010\)](#) and further modelled by [Bogouslavsky \(2016\)](#) in markets outside the United States. The pattern is observed in UK, Brazil, B-shares and in Hong Kong listed Chinese H-shares and exhibits all similarities to the pattern observed by [Heston, Korajczyk, and Sadka \(2010\)](#). It further proves that [HKS \(2010\)](#) intraday momentum pattern is not a product of data snooping etcetera as discussed by [Heston and Sadka \(2010\)](#) when they find international evidence for the existence of return seasonality using longer horizon data on International Markets. However, the evidence on the existence of the pattern in Chinese A-shares indicates that it manifests itself with a much weaker magnitude.

We are able to explain the weakness of the pattern in Chinese A-shares and the proliferation of the pattern in Chinese B-shares by virtue of difference in investor composition. The Chinese A-shares market is dominated by domestic individual investors ([Nartea, Kong, and Wu \(2017\)](#)) while the Chinese B-shares market is dominated by foreign institutional investors ([Chui and Titman \(2017b\)](#)). Since the dual listed B-shares exhibit the pattern more strongly in terms of cross sectional regression coefficients we infer that the investor composition plays an important role in the propagation of the pattern. This is in line with the studies like [Kaniel, Saar, and Titman \(2008\)](#) and [Baltzer, Jank, and Smajlbegovic \(2018\)](#) that claim that individual investors are contrarians and institutional investors engage in momentum strategies.

Furthermore, with regards to China, the pattern manifests itself as best as it can given the level of trading restrictions. These trading restrictions have raised a lot of debate in recent years as some studies like [Gu, Kang, and Xu \(2018\)](#) have argued that

these restrictions actually hurt markets and hamper market efficiency. We provide specific evidence with regards to price limits and day trading restrictions. We show that if we remove the top and bottom deciles from our sample, the remaining stocks are less prone to hitting price limits and the sample behaves more like the U.S and UK, Brazil and dual listed B and H-shares and the [HKS \(2010\)](#) pattern that we are studying here is more profound. This provides some evidence that limits of arbitrage act as a deterrent for institutional investors who deviate from their usual momentum trading behaviour.

We provide evidence in to the impact of the partial inclusion of A-shares in to the highly coveted MSCI Emerging Markets Index and show that it increases the level of institutional ownership, number of participating institutions, the percentage float held by institutions and foreign ownership in the included stocks. We use this inclusion as an exogenous shock to the level of institutional ownership in the 232 A-shares stocks. We show that after the inclusion in the index, the 232 A-shares demonstrate existence of the pattern that is closer to the US, UK, Brazil and the dual listed B- and H-shares. This further confirms the role of institutional investors in explaining the intraday momentum effect.

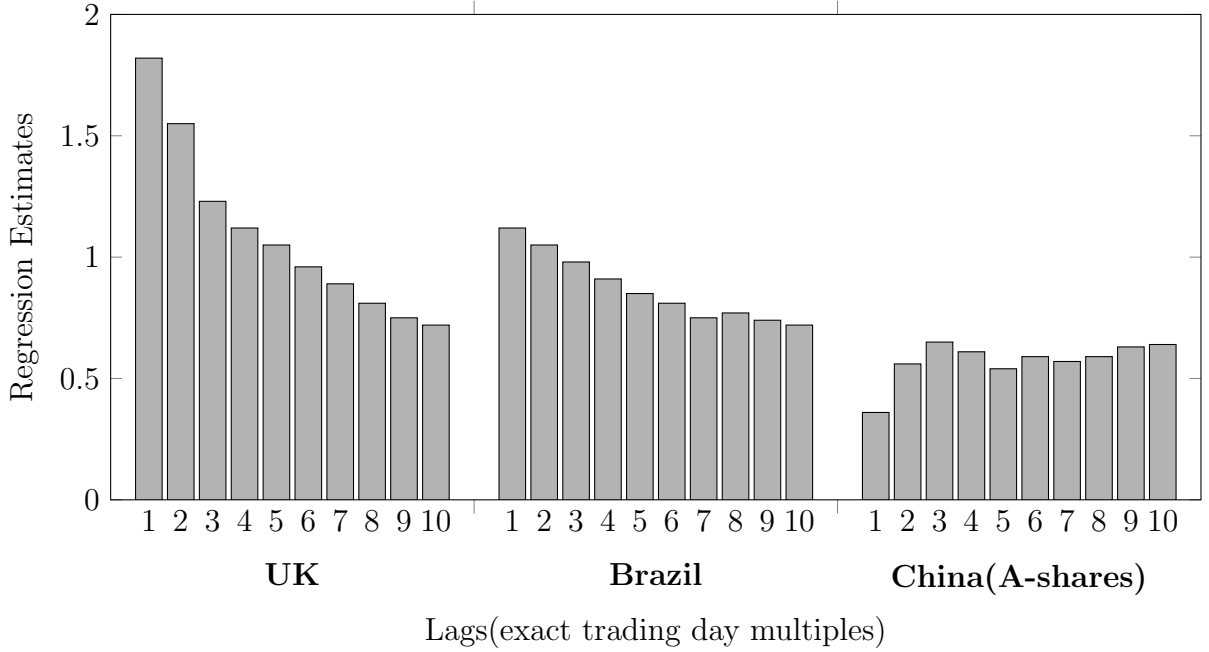
We show that at intervals just beyond daily multiples of the trading day, we see extreme evidence of return reversals. This shows that retail investors desperately wait to reverse short term positions and rush to reverse their positions as soon the 24 hour limit passes. It can actually lead to lots of selling pressure and market volatility. This is once again in line with the studies like [Kaniel, Saar, and Titman \(2008\)](#) and [Baltzer, Jank, and Smajlbegovic \(2018\)](#) that claim that individual investors are contrarians. Since, our A-shares investors are mostly domestic individual investors ([Nartea, Kong, and Wu \(2017\)](#)) we can say that our results are in line with the existing evidence. These findings also have implications from a regulatory perspective.

We find that the manifestation of the pattern is subject to the size of the firms. We find that large market capitalization group exhibits the intraday momentum pattern with the greatest strength owing to the tendency of institutional investors to herd in large stocks ([Li and Wang \(2010\)](#)). We do however, find that the time of the day explains the majority of the existence of the pattern. If we remove the first and last trading intervals, the pattern almost diminishes. Also, a portfolio analyses conducted in the spirit of [Jegadeesh and Titman \(1993\)](#) reveals that the returns on top minus bottom decile portfolios sorted by past half hour returns and held on for the next forty days have positive but significant returns, but are mostly weaker than the US, UK, Brazil and dual listed B- and H-share

counterparts. Consistent with our findings, [Chui and Titman \(2017b\)](#) find that over the longer horizon the momentum effect is more prevalent in Chinese B-shares than in their A-share counterparts. Our evidence further supports the findings of [Chui and Titman \(2017b\)](#).

Overall, our study also provides evidence that the tireless efforts of the Chinese regulators and policy makers to institutionalize the Chinese A-shares market is bearing fruit. Indeed, the plan for inclusion of 168 mid-cap stocks has been fast tracked and our results show that the dawn of a new era in Chinese stock markets has begun. In this era, the market will mature and will continue to get institutionalized gradually and move away from the ‘casino’ like features that it has come to be associated with. Future research should focus on providing empirical evidence regarding all the positive benefits of institutional investors in the context of China.

Figure 1.1: Manifestation of the Intraday Pattern Across Various Markets



This figure shows the regression coefficients for the cross-sectional regression as modelled by the equation $R_{i,t} = \alpha_{k,t} + \beta_{k,t}R_{i,t-k} + \epsilon_{i,t}$. The variable $R_{i,t}$ is the return on the stock in a particular half hour interval of the trading day. Whereas, $R_{i,t-k}$ is the lagged return of the same stock during the same half hour interval in exact multiples of a trading day for upto 10 days. The time-series average of the regression coefficients are reported in percentages in Panel A. The corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported in Panel B for each respective regression coefficient. The sample contains 3473 Chinese A-shares which trade from 9:30-11:00 am and from 1:00 to 3:00 pm, for the 1457 UK shares this interval is from 8:00 am to 4:30 pm and for Brazil's 365 stocks in our sample this interval is from 10:00 am to 5:55 pm.

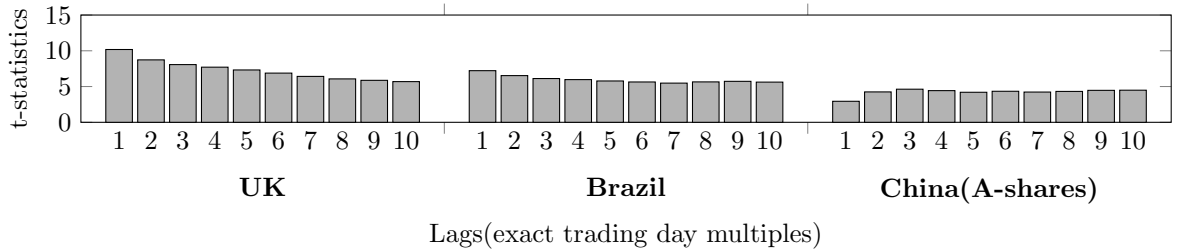
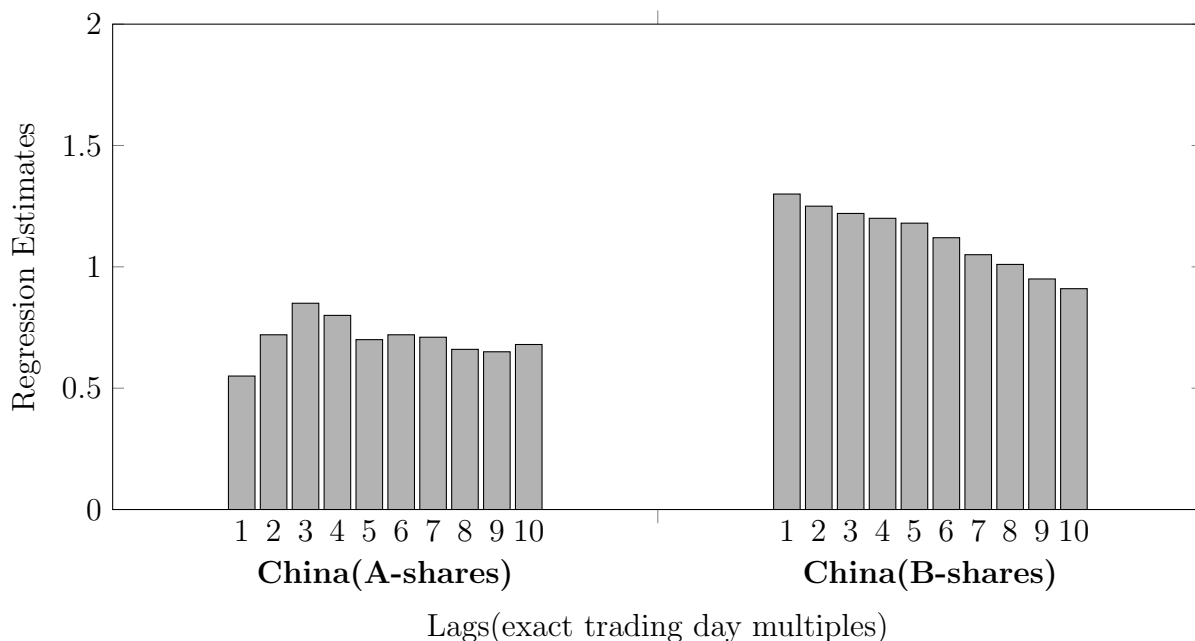


Figure 1.2: Relative Strength of the Intraday Pattern in 84 Dual Listed A-Shares and their corresponding B-Shares



This figure shows the regression coefficients for the cross-sectional regression as modelled by the equation $R_{i,t} = \alpha_{k,t} + \beta_{k,t}R_{i,t-k} + \epsilon_{i,t}$. The variable $R_{i,t}$ is the return on the stock in a particular half hour interval of the trading day. Whereas, $R_{i,t-k}$ is the lagged return of the same stock during the same half hour interval in exact multiples of a trading day for upto 10 days. The time-series average of the regression coefficients are reported in percentages in Panel A. The corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported in Panel B for each respective regression coefficient. The sample comprises 84 dual listed A-shares and their B-share counterparts.

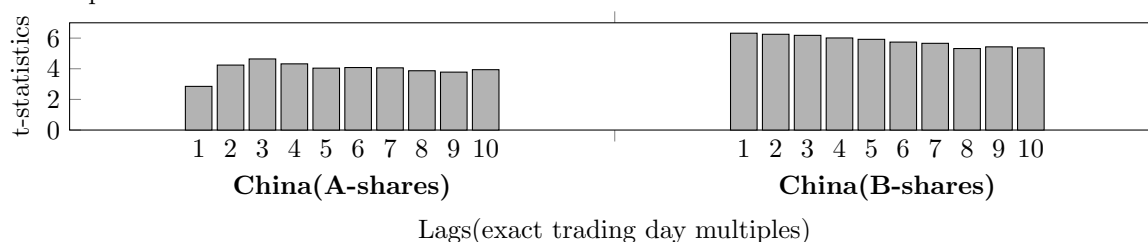
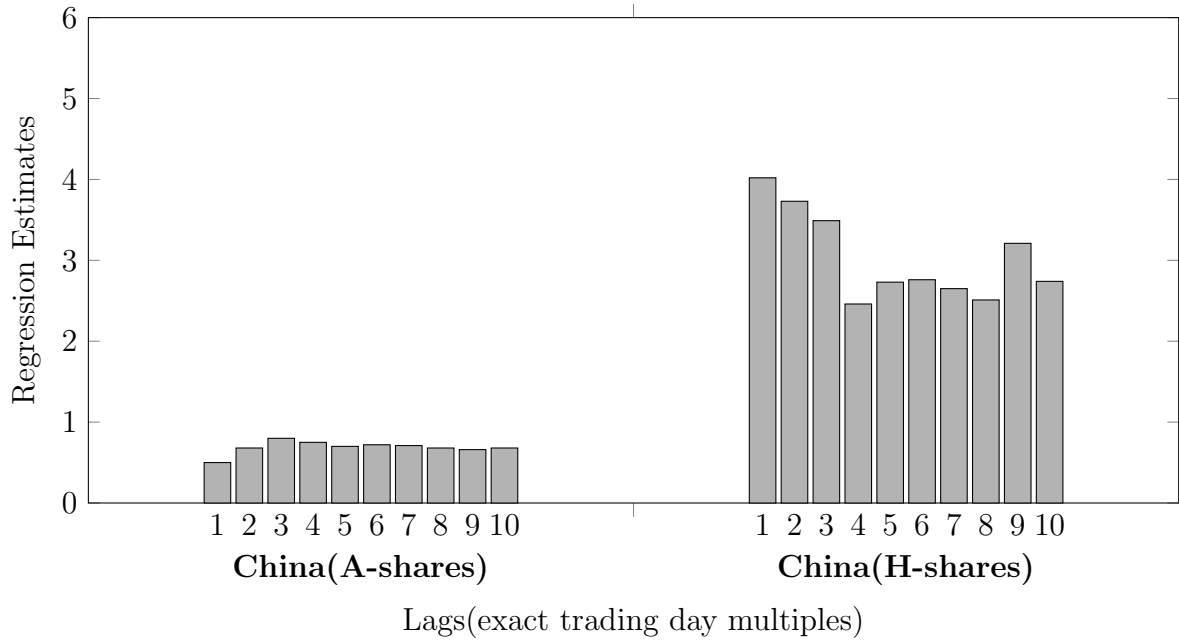


Figure 1.3: Relative Strength of the Pattern in 87 A-Shares and their cross listed H-Share Counterparts



This figure shows the regression coefficients for the cross-sectional regression as modelled by the equation $R_{i,t} = \alpha_{k,t} + \beta_{k,t}R_{i,t-k} + \epsilon_{i,t}$. The variable $R_{i,t}$ is the return on the stock in a particular half hour interval of the trading day. Whereas, $R_{i,t-k}$ is the lagged return of the same stock during the same half hour interval in exact multiples of a trading day for upto 10 days. The time-series average of the regression coefficients are reported in percentages in Panel A. The corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported in Panel B for each respective regression coefficient. The sample comprises 87 dual listed A-shares and their H-share counterparts.

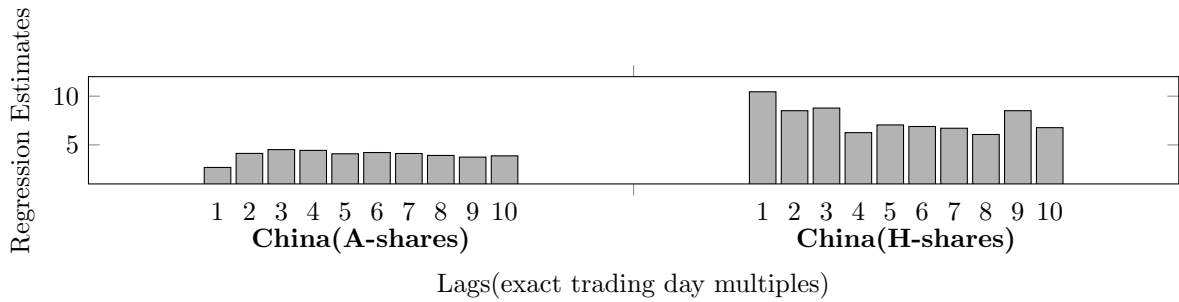
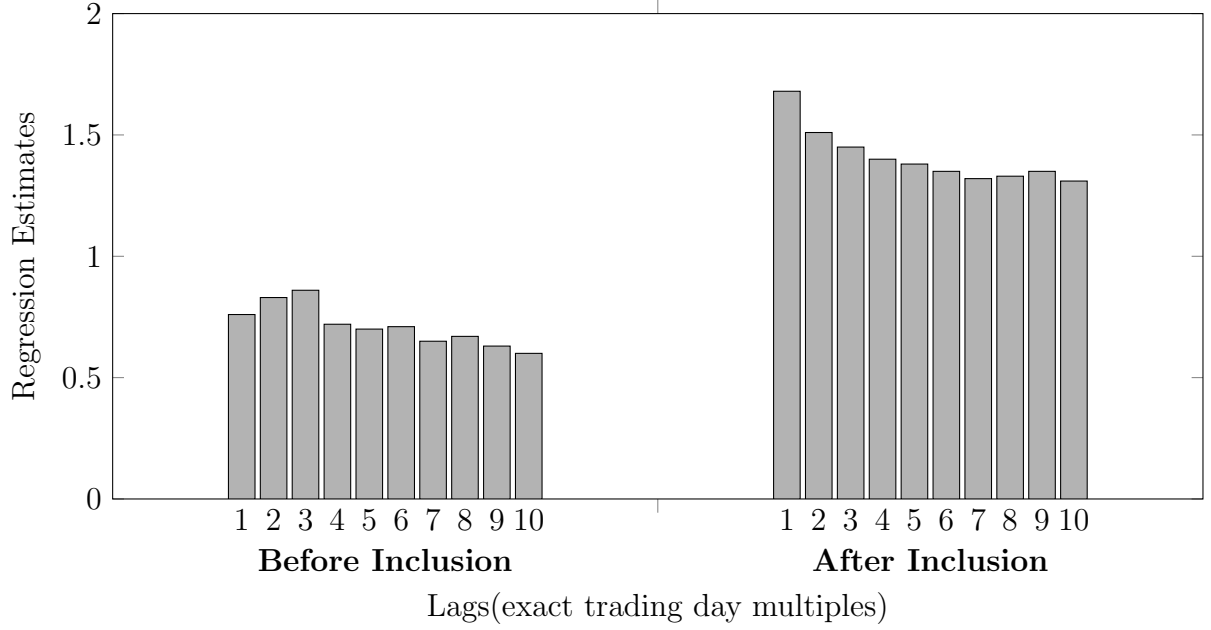


Figure 1.4: The Impact of Index Inclusion



This figure shows the regression coefficients for the cross-sectional regression as modelled by the equation $R_{i,t} = \alpha_{k,t} + \beta_{k,t}R_{i,t-k} + \epsilon_{i,t}$. The variable $R_{i,t}$ is the return on the stock in a particular half hour interval of the trading day. Whereas, $R_{i,t-k}$ is the lagged return of the same stock during the same half hour interval in exact multiples of a trading day for upto 10 days. The time-series average of the regression coefficients are reported in percentages in Panel A. The corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported in Panel B for each respective regression coefficient. The sample comprises 232 A-shares that were included in the Morgan Stanley Capital International (MSCI) index on June 1, 2018. We depict the regression estimates before and after the inclusion in the index to demonstrate the impact of the inclusion.

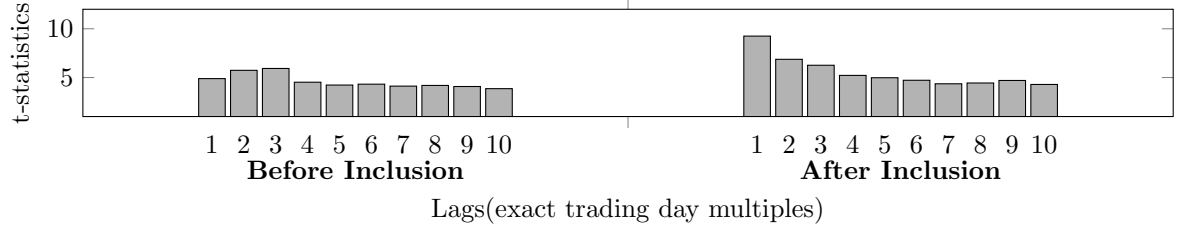
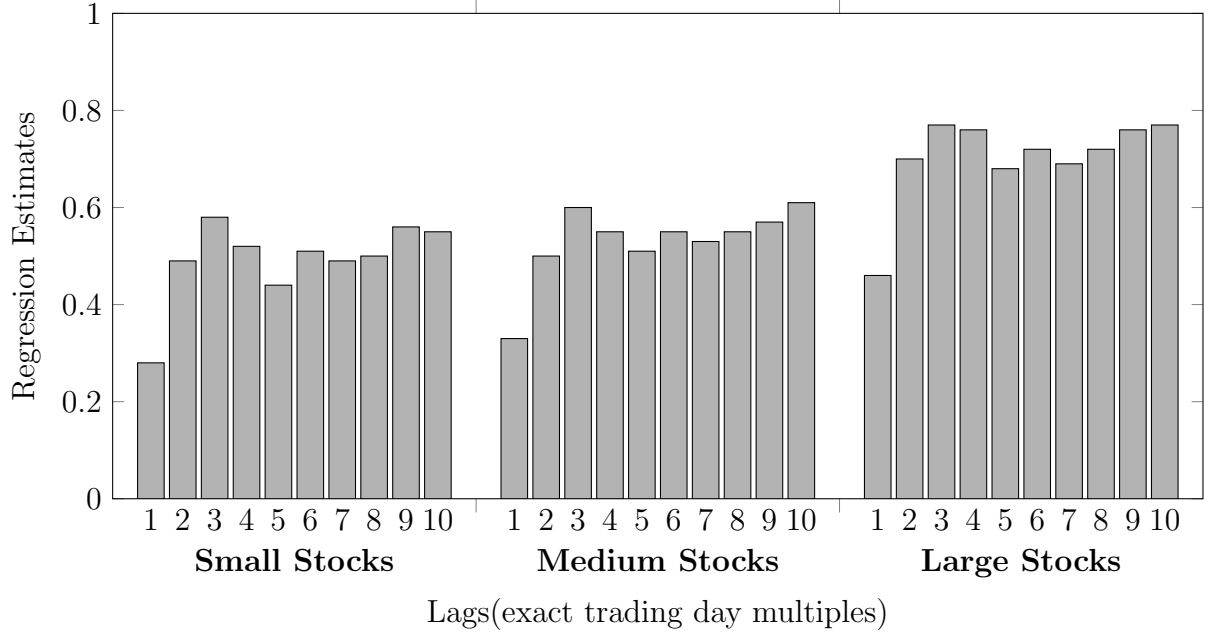


Figure 1.5: The Impact of Size on Intraday Momentum



This figure shows the regression coefficients for the cross-sectional regression as modelled by the equation $R_{i,t} = \alpha_{k,t} + \beta_{k,t}R_{i,t-k} + \epsilon_{i,t}$. The variable $R_{i,t}$ is the return on the stock in a particular half hour interval of the trading day. Whereas, $R_{i,t-k}$ is the lagged return of the same stock during the same half hour interval in exact multiples of a trading day for upto 10 days. The time-series average of the regression coefficients are reported in percentages in Panel A. The corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported in Panel B for each respective regression coefficient. The sample comprises 232 A-shares that were included in the Morgan Stanley Capital International (MSCI) index on June 1, 2018. We depict the regression estimates before and after the inclusion in the index to demonstrate the impact of the inclusion.

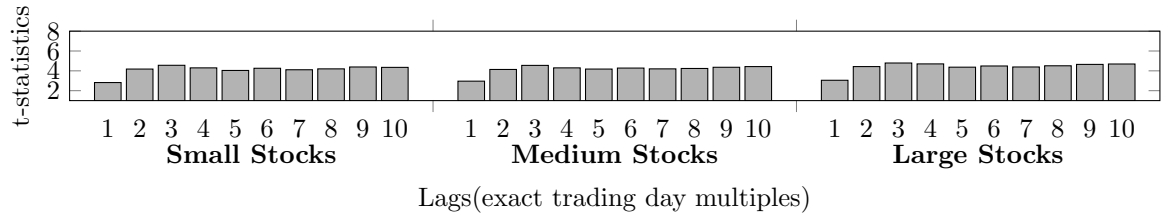


Table 1.1 : Various Share Classes

This table reports salient features of various share classes such as investor composition and trading regulations across them. It also outlines who is allowed to own the stocks in each share class as China places various restrictions on different share classes.

Type	Exchange	Primary Owners	Domestic/Foreign	Price Limits	Intraday Trading	Currency
A-shares	Shanghai/Shenzen	Individuals	Domestic	Yes	Not Allowed	RMB
B-shares	Shanghai/Shenzen	Institutional	Foreign	Yes	Not Allowed	USD/HKD
H-shares	Hong Kong	Institutional	Foreign	No	Allowed	HKD

Table 1.2 : Summary Statistics

This table reports the number of stocks from each category which are included in our sample based on the criteria of atleast 50 trades every year. It also reports the mean market capitalization for each category. The mean returns for the thirty minute interval in basis points and their standard deviation in percentage is also reported .

Country	Type	Number of Stocks	Mean Market Cap (Billions)	Mean Returns (Basis Points)	Standard Deviation
China	A-shares(All)	3473	17.25	0.008	0.007
China	A-shares(small)	1157	3.40	0.010	0.009
China	A-shares(medium)	1157	6.78	0.009	0.008
China	A-shares(large)	1158	40.32	0.007	0.006
China	B-shares(dual-listed)	84	10.25	0.006	0.006
China	H-shares(dual-listed)	87	15.12	0.007	0.008
UK	Common Stock	1457	1.67	0.006	0.009
Brazil	Common Stock	365	7.62	0.007	0.008

Table 1.3 : Cross Sectional Regressions

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. The trading day is divided into non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. For the UK and Brazil, the trading day runs from 8:00 am to 4:30 pm and from 10:00 am to 5:55 pm respectively. The UK sample contains all 1457 firms and Brazil contains all 365 firms. A procedure similar to that applied to the Chinese firms is followed for the UK as well as Brazil. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding Fama and Macbeth (1973) t-statistics are reported along side. In the second row below the raw regression estimates the standardized estimates are also reported.

All Chinese A-shares					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.36	2.94	21 Days	0.42	3.16
	0.18			0.23	
2 Days	0.56	4.25	22 Days	0.43	3.29
	0.29			0.20	
3 Days	0.65	4.63	23 Days	0.44	3.35
	0.33			0.23	
4 Days	0.61	4.43	24 Days	0.48	3.64
	0.30			0.24	
5 Days	0.54	4.20	25 Days	0.48	3.62
	0.27			0.23	
6 Days	0.59	4.34	26 Days	0.46	3.42
	0.29			0.24	
7 Days	0.57	4.23	27 Days	0.47	3.47
	0.28			0.24	
8 Days	0.59	4.32	28 Days	0.35	2.78
	0.29			0.19	
9 Days	0.63	4.47	29 Days	0.37	2.90
	0.32			0.20	
10 Days	0.64	4.49	30 Days	0.30	2.56
	0.33			0.15	
11 Days	0.44	3.44	31 Days	0.33	2.69
	0.22			0.16	
12 Days	0.61	4.38	32 Days	0.33	2.67
	0.31			0.17	
13 Days	0.40	3.11	33 Days	0.31	2.57
	0.20			0.15	
14 Days	0.51	3.93	34 Days	0.31	2.53
	0.25			0.15	
15 Days	0.50	3.80	35 Days	0.30	2.47
	0.24			0.14	
16 Days	0.36	2.84	36 Days	0.27	2.35
	0.18			0.14	
17 Days	0.43	3.31	37 Days	0.25	2.28
	0.22			0.13	
18 Days	0.46	3.50	38 Days	0.23	2.14
	0.22			0.12	
19 Days	0.37	2.93	39 Days	0.26	2.31
	0.19			0.13	
20 Days	0.47	3.54	40 Days	0.23	2.11
	0.23			0.11	

(Continued)

Table 1.3 – *Continued*

The United Kingdom					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	1.82	10.18	21 Days	0.56	5.33
	0.81			0.28	
2 Days	1.55	8.73	22 Days	0.51	5.01
	0.73			0.26	
3 Days	1.23	8.07	23 Days	0.45	4.96
	0.60			0.22	
4 Days	1.12	7.71	24 Days	0.50	5.25
	0.56			0.24	
5 Days	1.05	7.32	25 Days	0.57	6.67
	0.52			0.27	
6 Days	0.96	6.88	26 Days	0.56	5.39
	0.47			0.27	
7 Days	0.89	6.42	27 Days	0.55	5.25
	0.44			0.26	
8 Days	0.81	6.07	28 Days	0.48	4.56
	0.40			0.24	
9 Days	0.75	5.87	29 Days	0.56	5.74
	0.37			0.28	
10 Days	0.72	5.69	30 Days	0.54	5.45
	0.36			0.27	
11 Days	0.68	5.59	31 Days	0.53	5.24
	0.34			0.26	
12 Days	0.63	5.41	32 Days	0.41	4.85
	0.32			0.20	
13 Days	0.60	4.89	33 Days	0.36	4.14
	0.30			0.18	
14 Days	0.77	5.45	34 Days	0.37	3.78
	0.37			0.18	
15 Days	0.61	5.22	35 Days	0.34	3.89
	0.37			0.18	
16 Days	0.55	4.84	36 Days	0.40	4.38
	0.27			0.20	
17 Days	0.51	4.78	37 Days	0.36	3.39
	0.26			0.18	
18 Days	0.46	4.70	38 Days	0.44	3.51
	0.24			0.22	
19 Days	0.47	4.43	39 Days	0.53	3.94
	0.23			0.26	
20 Days	0.53	4.56	40 Days	0.48	3.23
	0.26			0.24	

(Continued)

Table 1.3 – *Continued*

Brazil					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	1.12	7.22	21 Days	0.46	4.32
	0.60			0.24	
2 Days	1.05	6.53	22 Days	0.44	4.25
	0.55			0.23	
3 Days	0.98	6.12	23 Days	0.45	4.30
	0.53			0.23	
4 Days	0.91	5.97	24 Days	0.40	3.84
	0.50			0.22	
5 Days	0.85	5.78	25 Days	0.41	3.92
	0.46			0.22	
6 Days	0.81	5.64	26 Days	0.39	3.80
	0.44			0.21	
7 Days	0.75	5.48	27 Days	0.37	3.62
	0.42			0.20	
8 Days	0.77	5.65	28 Days	0.35	3.45
	0.40			0.19	
9 Days	0.74	5.73	29 Days	0.40	3.83
	0.38			0.21	
10 Days	0.72	5.62	30 Days	0.44	4.23
	0.37			0.23	
11 Days	0.65	5.23	31 Days	0.43	4.17
	0.33			0.23	
12 Days	0.55	5.12	32 Days	0.35	3.44
	0.30			0.19	
13 Days	0.58	4.63	33 Days	0.33	3.40
	0.31			0.17	
14 Days	0.64	5.20	34 Days	0.34	3.42
	0.33			0.18	
15 Days	0.59	5.15	35 Days	0.30	3.23
	0.30			0.16	
16 Days	0.52	4.61	36 Days	0.31	3.31
	0.28			0.16	
17 Days	0.55	4.87	37 Days	0.34	3.40
	0.30			0.17	
18 Days	0.48	4.44	38 Days	0.28	3.14
	0.25			0.15	
19 Days	0.47	4.38	39 Days	0.29	3.20
	0.26			0.15	
20 Days	0.45	4.29	40 Days	0.27	3.12
	0.23			0.15	

Table 1.4 : 84- Dual Listed A- and B-Shares

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. Out of these we have 88 shares that are dual listed as A and B-shares both. The trading day is divided into non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding ([Fama and MacBeth, 1973](#)) t-statistics are reported along side. The table reports results for dual listed A and B-shares. There are a total of 84 of these in our sample. In the second row below the raw regression estimates the standardized estimates are also reported.

Dual Listed Chinese A-shares					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.55	2.85	21 Days	0.49	3.08
	0.26			0.23	
2 Days	0.72	4.24	22 Days	0.51	3.19
	0.35			0.27	
3 Days	0.85	4.64	23 Days	0.48	3.02
	0.41			0.23	
4 Days	0.80	4.32	24 Days	0.47	2.95
	0.39			0.22	
5 Days	0.70	4.04	25 Days	0.50	3.09
	0.38			0.23	
6 Days	0.72	4.08	26 Days	0.46	2.87
	0.34			0.22	
7 Days	0.71	4.06	27 Days	0.45	2.76
	0.34			0.21	
8 Days	0.66	3.87	28 Days	0.42	2.54
	0.32			0.20	
9 Days	0.65	3.78	29 Days	0.51	2.97
	0.32			0.23	
10 Days	0.68	3.94	30 Days	0.40	2.36
	0.33			0.19	
11 Days	0.60	3.54	31 Days	0.43	2.42
	0.28			0.20	
12 Days	0.62	3.62	32 Days	0.45	2.45
	0.30			0.21	
13 Days	0.58	3.41	33 Days	0.48	2.98
	0.28			0.22	
14 Days	0.59	3.44	34 Days	0.46	2.77
	0.28			0.21	
15 Days	0.65	3.69	35 Days	0.42	2.37
	0.31			0.20	
16 Days	0.52	3.26	36 Days	0.45	2.40
	0.25			0.21	
17 Days	0.55	3.31	37 Days	0.40	2.26
	0.26			0.19	
18 Days	0.50	3.18	38 Days	0.44	2.33
	0.24			0.21	
19 Days	0.52	3.22	39 Days	0.38	2.14
	0.25			0.18	
20 Days	0.60	3.44	40 Days	0.32	2.03
	0.28			0.15	

(Continued)

Table 1.4 – Continued

Dual Listed Chinese B-shares					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	1.30	6.32	21 Days	0.60	4.44
	0.67			0.32	
2 Days	1.25	6.25	22 Days	0.56	4.32
	0.65			0.30	
3 Days	1.22	6.18	23 Days	0.58	4.39
	0.63			0.31	
4 Days	1.20	6.01	24 Days	0.55	3.63
	0.62			0.29	
5 Days	1.18	5.92	25 Days	0.51	3.52
	0.61			0.27	
6 Days	1.12	5.74	26 Days	0.50	3.47
	0.61			0.27	
7 Days	1.05	5.66	27 Days	0.47	3.39
	0.56			0.25	
8 Days	1.01	5.52	28 Days	0.45	3.27
	0.56			0.25	
9 Days	0.95	5.43	29 Days	0.46	3.30
	0.54			0.24	
10 Days	0.91	5.36	30 Days	0.44	3.19
	0.52			0.24	
11 Days	0.89	5.26	31 Days	0.43	3.15
	0.51			0.23	
12 Days	0.85	5.17	32 Days	0.41	2.91
	0.49			0.22	
13 Days	0.84	5.09	33 Days	0.37	2.73
	0.47			0.20	
14 Days	0.80	4.95	34 Days	0.41	2.88
	0.45			0.22	
15 Days	0.77	4.89	35 Days	0.35	2.63
	0.43			0.20	
16 Days	0.75	4.81	36 Days	0.36	2.65
	0.42			0.21	
17 Days	0.71	4.72	37 Days	0.32	2.57
	0.40			0.18	
18 Days	0.68	4.65	38 Days	0.30	2.48
	0.38			0.17	
19 Days	0.66	4.58	39 Days	0.29	2.43
	0.37			0.16	
20 Days	0.62	4.51	40 Days	0.27	2.36
	0.35			0.15	

Table 1.5 : 87-Cross Listed A- and H-Shares

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. Out of these we pick the 87 stocks that are also cross listed in Hong Kong and trade as H-shares. The trading day is divided into non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. For the H-listed shares in Hong Kong the trading hours are 9:30 am to 4:00 pm, corresponding to 13 half hour intervals every day. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding [Fama and MacBeth \(1973\)](#) t-statistics are reported along side. In the second row below the raw regression estimates the standardized estimates are also reported.

The Chinese A-Shares					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.50	2.69	21 Days	0.48	2.76
	0.23			0.22	
2 Days	0.68	4.13	22 Days	0.50	2.79
	0.32			0.23	
3 Days	0.80	4.52	23 Days	0.48	2.70
	0.38			0.23	
4 Days	0.75	4.44	24 Days	0.46	2.62
	0.36			0.21	
5 Days	0.70	4.09	25 Days	0.51	2.80
	0.34			0.24	
6 Days	0.72	4.22	26 Days	0.47	2.65
	0.35			0.22	
7 Days	0.71	4.12	27 Days	0.50	2.72
	0.35			0.23	
8 Days	0.68	3.92	28 Days	0.45	2.49
	0.33			0.22	
9 Days	0.66	3.75	29 Days	0.44	2.42
	0.32			0.21	
10 Days	0.68	3.88	30 Days	0.36	2.19
	0.33			0.17	
11 Days	0.63	3.51	31 Days	0.40	2.28
	0.30			0.19	
12 Days	0.60	3.35	32 Days	0.37	2.21
	0.28			0.18	
13 Days	0.59	3.23	33 Days	0.40	2.23
	0.27			0.19	
14 Days	0.57	3.14	34 Days	0.35	2.08
	0.25			0.16	
15 Days	0.60	3.31	35 Days	0.34	2.01
	0.27			0.15	
16 Days	0.55	3.02	36 Days	0.35	2.03
	0.26			0.16	
17 Days	0.54	2.95	37 Days	0.36	2.09
	0.25			0.17	
18 Days	0.57	3.08	38 Days	0.35	2.01
	0.27			0.16	
19 Days	0.55	3.00	39 Days	0.38	2.22
	0.26			0.17	
20 Days	0.52	2.85	40 Days	0.36	2.04
	0.25			0.16	

(Continued)

Table 1.5 – *Continued*

The Chinese H-Shares					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	4.02 0.85	10.45	21 Days	2.39 0.49	6.08
2 Days	3.73 0.81	8.51	22 Days	2.12 0.46	5.30
3 Days	3.49 0.78	8.78	23 Days	2.15 0.46	5.52
4 Days	2.46 0.66	6.26	24 Days	2.33 0.48	5.80
5 Days	2.73 0.69	7.05	25 Days	2.18 0.45	5.23
6 Days	2.76 0.70	6.89	26 Days	1.47 0.32	3.59
7 Days	2.65 0.66	6.71	27 Days	1.56 0.33	3.87
8 Days	2.51 0.62	6.07	28 Days	1.29 0.30	3.25
9 Days	3.21 0.71	8.51	29 Days	2.07 0.39	5.21
10 Days	2.74 0.68	6.77	30 Days	1.63 0.38	3.90
11 Days	2.85 0.72	7.03	31 Days	1.35 0.32	3.39
12 Days	1.92 0.40	5.10	32 Days	1.75 0.39	3.97
13 Days	2.60 0.64	6.83	33 Days	1.47 0.39	3.57
14 Days	2.44 0.60	6.26	34 Days	1.54 0.39	3.58
15 Days	2.43 0.59	6.14	35 Days	1.43 0.38	3.51
16 Days	2.12 0.43	5.26	36 Days	1.23 0.30	2.69
17 Days	1.54 0.39	4.06	37 Days	1.45 0.38	3.90
18 Days	2.09 0.43	5.20	38 Days	1.59 0.38	3.69
19 Days	2.03 0.42	4.90	39 Days	1.45 0.37	3.35
20 Days	1.53 0.38	3.73	40 Days	1.51 0.37	3.37

Table 1.6 : Intraday Momentum and Size

This table reports the results for our all A-share sample separated in to small, medium and large stocks by market capitalization to study the impact of size on the existence of the pattern. The results are reported for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. These are then split in to 1157 stocks in the small and medium firm categories and 1158 in the large cap category of firms. The trading day is divided in to non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding ([Fama and MacBeth, 1973](#)) t-statistics are reported along side. In the second row below the raw regression estimates the standardized estimates are also reported.

Small Cap Firms					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.28	2.82	21 Days	0.34	2.94
	0.12			0.15	
2 Days	0.49	4.18	22 Days	0.35	3.15
	0.26			0.15	
3 Days	0.58	4.56	23 Days	0.36	3.18
	0.23			0.16	
4 Days	0.52	4.30	24 Days	0.42	3.60
	0.23			0.19	
5 Days	0.44	4.04	25 Days	0.50	4.15
	0.23			0.19	
6 Days	0.51	4.26	26 Days	0.41	3.50
	0.22			0.18	
7 Days	0.49	4.11	27 Days	0.43	3.62
	0.21			0.19	
8 Days	0.50	4.20	28 Days	0.20	2.42
	0.21			0.09	
9 Days	0.56	4.39	29 Days	0.32	2.84
	0.23			0.13	
10 Days	0.55	4.35	30 Days	0.18	2.36
	0.24			0.08	
11 Days	0.35	3.17	31 Days	0.29	2.88
	0.15			0.12	
12 Days	0.54	4.32	32 Days	0.30	2.91
	0.22			0.13	
13 Days	0.33	2.90	33 Days	0.27	2.76
	0.14			0.11	
14 Days	0.44	3.77	34 Days	0.25	2.52
	0.18			0.10	
15 Days	0.43	3.66	35 Days	0.23	2.45
	0.18			0.10	
16 Days	0.30	2.77	36 Days	0.20	2.35
	0.12			0.09	
17 Days	0.34	3.16	37 Days	0.19	2.29
	0.15			0.09	
18 Days	0.41	3.55	38 Days	0.18	2.02
	0.17			0.08	
19 Days	0.31	2.80	39 Days	0.20	2.33
	0.15			0.09	
20 Days	0.40	3.47	40 Days	0.19	2.09
	0.18			0.08	

(Continued)

Table 1.6 – Continued

Medium Cap Firms					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.33	2.96	21 Days	0.38	3.28
	0.17			0.19	
2 Days	0.50	4.14	22 Days	0.40	3.37
	0.25			0.20	
3 Days	0.60	4.55	23 Days	0.41	3.40
	0.30			0.21	
4 Days	0.55	4.30	24 Days	0.45	3.75
	0.28			0.23	
5 Days	0.51	4.18	25 Days	0.32	2.78
	0.26			0.16	
6 Days	0.55	4.28	26 Days	0.42	3.46
	0.28			0.21	
7 Days	0.53	4.20	27 Days	0.36	3.02
	0.27			0.18	
8 Days	0.55	4.24	28 Days	0.30	2.69
	0.28			0.15	
9 Days	0.57	4.36	29 Days	0.31	2.72
	0.28			0.16	
10 Days	0.61	4.43	30 Days	0.29	2.52
	0.31			0.15	
11 Days	0.42	3.61	31 Days	0.27	2.41
	0.21			0.14	
12 Days	0.58	4.40	32 Days	0.26	2.37
	0.29			0.13	
13 Days	0.36	3.17	33 Days	0.25	2.31
	0.18			0.25	
14 Days	0.45	3.81	34 Days	0.29	2.48
	0.23			0.15	
15 Days	0.44	3.72	35 Days	0.24	2.25
	0.22			0.12	
16 Days	0.32	2.81	36 Days	0.22	2.17
	0.16			0.11	
17 Days	0.41	3.45	37 Days	0.21	2.09
	0.21			0.11	
18 Days	0.42	3.58	38 Days	0.20	2.06
	0.21			0.10	
19 Days	0.33	2.89	39 Days	0.24	2.22
	0.17			0.12	
20 Days	0.42	3.50	40 Days	0.19	2.01
	0.21			0.20	

(Continued)

Table 1.6 – *Continued*

The Large Cap Firms					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.46	3.05	21 Days	0.54	3.26
	0.28			0.32	
2 Days	0.70	4.43	22 Days	0.55	3.35
	0.42			0.33	
3 Days	0.77	4.79	23 Days	0.56	3.48
	0.47			0.34	
4 Days	0.76	4.70	24 Days	0.58	3.57
	0.46			0.35	
5 Days	0.68	4.37	25 Days	0.62	3.94
	0.41			0.36	
6 Days	0.72	4.49	26 Days	0.55	3.31
	0.43			0.33	
7 Days	0.69	4.39	27 Days	0.61	3.77
	0.41			0.36	
8 Days	0.72	4.51	28 Days	0.54	3.22
	0.43			0.32	
9 Days	0.76	4.65	29 Days	0.48	3.15
	0.46			0.29	
10 Days	0.77	4.69	30 Days	0.45	2.82
	0.47			0.27	
11 Days	0.56	3.54	31 Days	0.43	2.79
	0.34			0.25	
12 Days	0.71	4.43	32 Days	0.43	2.72
	0.42			0.25	
13 Days	0.51	3.26	33 Days	0.41	2.65
	0.31			0.24	
14 Days	0.65	4.22	34 Days	0.40	2.60
	0.39			0.24	
15 Days	0.63	4.02	35 Days	0.42	2.70
	0.38			0.25	
16 Days	0.46	2.95	36 Days	0.38	2.52
	0.27			0.23	
17 Days	0.54	3.31	37 Days	0.36	2.46
	0.32			0.14	
18 Days	0.55	3.38	38 Days	0.31	2.33
	0.32			0.14	
19 Days	0.47	3.09	39 Days	0.33	2.38
	0.29			0.19	
20 Days	0.59	3.67	40 Days	0.31	2.28
	0.35			0.18	

Table 1.7 : Intraday Momentum and Time of Day

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3238 firms. The first and the last intervals are excluded for each trading day and the analyses is carried out. The trading day is divided in to non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. However, dropping the first and last half hour leaves us with 6 half-hour intervals only. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding ([Fama and MacBeth, 1973](#)) t-statistics are reported along side. In the second row below the raw regression estimates the standardized estimates are also reported.

The Chinese A-Shares

Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1	0.13 0.07	1.20	21	0.25 0.15	1.93
2	0.18 0.09	1.82	22	0.27 0.16	1.96
3	0.37 0.19	2.58	23	0.25 0.15	1.87
4	0.39 0.20	2.74	24	0.24 0.14	1.72
5	0.30 0.17	2.25	25	0.23 0.12	1.65
6	0.28 0.16	2.03	26	0.22 0.12	1.59
7	0.29 0.16	2.11	27	0.21 0.12	1.49
8	0.28 0.15	2.01	28	0.13 0.06	1.23
9	0.30 0.15	2.19	29	0.11 0.05	1.08
10	0.31 0.16	2.38	30	0.12 0.06	1.16
11	0.17 0.08	1.33	31	0.25 0.12	1.81
12	0.33 0.17	2.47	32	0.21 0.11	1.44
13	0.17 0.08	1.31	33	0.19 0.09	1.31
14	0.31 0.16	2.31	34	0.15 0.07	1.27
15	0.24 0.12	1.91	35	0.10 0.05	0.84
16	0.14 0.07	1.22	36	0.11 0.05	1.01
17	0.23 0.07	1.82	37	0.11 0.05	0.95
18	0.24 0.12	1.85	38	0.07 0.03	0.70
19	0.13 0.06	1.15	39	0.05 0.02	0.63
20	0.24 0.12	1.75	40	0.03 0.01	0.55

Table 1.8 : Controlling for Price Limits

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. The trading day is divided in to non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. Stocks are sorted in to top and bottom deciles at the end of every half hour interval based on returns and the top and bottom deciles are dropped. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding ([Fama and MacBeth, 1973](#)) t-statistics are reported along side. This table separates our all A-share sample in to small, medium and large stocks by market capitalization to study the impact of size on the existence of the pattern. In the second row below the raw regression estimates the standardized estimates are also reported.

The Chinese A-Shares

Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.52	4.92	21 Days	0.34	3.22
	0.27			0.17	
2 Days	0.51	4.86	22 Days	0.30	3.02
	0.26			0.15	
3 Days	0.65	7.21	23 Days	0.28	2.88
	0.34			0.15	
4 Days	0.51	4.41	24 Days	0.38	3.44
	0.26			0.20	
5 Days	0.53	3.97	25 Days	0.33	3.18
	0.27			0.17	
6 Days	0.55	4.65	26 Days	0.32	3.05
	0.28			0.16	
7 Days	0.45	4.08	27 Days	0.30	2.95
	0.23			0.16	
8 Days	0.43	3.99	28 Days	0.27	2.70
	0.22			0.14	
9 Days	0.52	4.52	29 Days	0.26	2.62
	0.27			0.13	
10 Days	0.50	4.32	30 Days	0.24	2.57
	0.26			0.12	
11 Days	0.41	3.85	31 Days	0.25	2.60
	0.22			0.13	
12 Days	0.49	4.23	32 Days	0.23	2.44
	0.25			0.12	
13 Days	0.39	3.62	33 Days	0.22	2.37
	0.20			0.11	
14 Days	0.49	4.18	34 Days	0.19	2.26
	0.25			0.10	
15 Days	0.45	4.03	35 Days	0.18	2.19
	0.23			0.09	
16 Days	0.32	3.13	36 Days	0.17	2.14
	0.16			0.09	
17 Days	0.38	3.49	37 Days	0.15	2.09
	0.19			0.08	
18 Days	0.45	5.00	38 Days	0.14	2.05
	0.23			0.07	
19 Days	0.36	3.26	39 Days	0.15	2.07
	0.18			0.08	
20 Days	0.39	3.57	40 Days	0.13	2.01
	0.20			0.07	

Table 1.9 : The Impact of Day Trading Rule

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period ranging from June 1, 2016 to March 1, 2019. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The sample consists of all stocks trading on all exchanges in China and the sample is obtained by matching stocks common in both our Bloomberg data and CSMAR data. The final sample contains 3473 firms. The trading day is divided into non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=1, 2, 3, 4$ and so on until 20 lags. For the UK there are 17 half hour intervals in the trading day, so 51 intervals make up for 3 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [HKS \(2010\)](#). Also, the corresponding ([Fama and MacBeth, 1973](#)) t-statistics are reported along side. First UK is reported, next China is reported. In the second row below the raw regression estimates the standardized estimates are also reported.

The United Kingdom

Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1	-0.23	-1.54	18	0.08	1.78	35	0.02	1.27
	-0.12			0.04			0.01	
2	0.25	2.46	19	0.07	1.70	36	0.05	1.58
	0.13			0.03			0.03	
3	0.24	2.42	20	0.12	2.02	37	0.01	1.19
	0.12			0.06			0.01	
4	0.20	2.31	21	0.11	1.97	38	0.03	1.41
	0.10			0.06			0.01	
5	0.18	2.26	22	0.13	2.06	39	0.03	1.38
	0.09			0.06			0.01	
6	0.17	2.22	23	0.02	1.32	40	0.01	1.16
	0.08			0.01			0.01	
7	0.15	2.17	24	0.10	1.93	41	0.02	1.25
	0.07			0.05			0.01	
8	0.14	2.12	25	0.08	1.81	42	0.01	1.12
	0.07			0.04			0.01	
9	0.15	2.14	26	0.18	2.23	43	0.01	1.09
	0.07			0.04			0.01	
10	0.13	2.10	27	0.19	2.28	44	0.03	1.35
	0.06			0.10			0.01	
11	0.12	2.05	28	0.17	2.20	45	0.04	1.47
	0.06			0.08			0.02	
12	0.11	2.00	29	0.16	2.19	46	0.02	1.23
	0.05			0.08			0.01	
13	0.10	1.95	30	0.14	2.13	47	0.01	1.02
	0.05			0.07			0.01	
14	0.09	1.89	31	0.12	2.02	48	0.03	1.33
	0.05			0.06			0.02	
15	0.08	1.84	32	0.13	2.08	49	0.02	1.21
	0.05			0.06			0.02	
16	0.12	2.03	33	0.10	1.91	50	0.06	1.62
	0.06			0.05			0.03	
17	1.80	10.18	34	1.55	8.73	51	1.23	8.07
	0.82			0.75			0.62	

(Continued)

Table 1.9 – *Continued*

China								
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1	-0.29	-2.09	9	-0.58	-7.14	17	-0.45	-4.36
	-0.15			-0.29			-0.23	
2	-0.20	-1.58	10	-0.18	-1.50	18	-0.15	-1.23
	-0.10			-0.09			-0.08	
3	0.16	1.42	11	0.10	0.62	19	0.09	0.55
	0.08			0.05			0.04	
4	0.14	0.98	12	0.12	0.72	20	0.08	0.56
	0.07			0.06			0.04	
5	0.20	1.99	13	0.14	0.93	21	0.12	0.60
	0.10			0.07			0.06	
6	0.24	2.42	14	0.22	2.26	22	0.18	1.76
	0.12			0.11			0.09	
7	0.43	3.31	15	0.26	2.65	23	0.25	2.49
	0.22			0.13			0.13	
8	0.36	2.94	16	0.56	4.03	24	0.65	4.63
	0.18			0.28			0.33	

Table 1.10 : High Minus Low Portfolio Returns

This table reports the performance for the portfolios formed on the basis of each half-hour interval's returns. The stocks are sorted every half hour and portfolios are formed using the top and bottom deciles and their half hour returns are observed for the next forty days(during the same half hour interval). All intervals from 8:00 to 16:30 are taken and stocks are sorted every half-hour. The sample period ranges from June 1, 2016 to March 1, 2019. The average return spreads(top minus bottom decile) on portfolios formed on the basis on the performance during the relevant historical half hour (with lags 1 to 40 days) interval are reported. The stocks are grouped in to ten portfolios with an equal number of stocks in each portfolio. The returns are reported in basis points.

The United Kingdom											
Lag(days)	Returns	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Returns	t-Statistic
1	4.04	13.65	11	1.17	4.02	21	0.58	1.95	31	0.58	1.89
2	3.11	10.53	12	0.67	2.29	22	0.70	2.37	32	0.30	1.01
3	2.40	8.23	13	0.72	2.48	23	0.61	2.16	33	0.68	2.33
4	2.01	7.25	14	0.39	1.35	24	0.69	2.40	34	0.26	0.88
5	1.55	5.40	15	0.52	1.78	25	0.44	1.53	35	0.49	1.65
6	1.26	4.36	16	0.75	2.57	26	0.47	1.61	36	0.26	0.85
7	1.24	4.30	17	0.80	2.71	27	0.49	1.67	37	0.06	0.15
8	1.18	4.15	18	0.69	2.45	28	0.07	0.24	38	0.46	1.55
9	1.30	4.53	19	0.22	0.76	29	0.06	0.20	39	0.32	1.05
10	0.70	2.50	20	0.65	2.23	30	0.84	2.82	40	0.52	1.71
Brazil											
Lag(days)	Returns	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Returns	t-Statistic
1	3.09	9.78	11	1.12	5.35	21	0.58	2.95	31	0.54	2.75
2	2.21	7.53	12	0.98	4.85	22	0.65	3.18	32	0.45	2.50
3	1.85	6.79	13	1.02	5.05	23	0.72	4.30	33	0.52	2.80
4	1.65	6.27	14	0.89	4.53	24	0.59	3.02	34	0.42	2.35
5	1.60	6.04	15	0.77	4.23	25	0.62	3.09	35	0.51	2.74
6	1.46	5.86	16	0.80	4.37	26	0.57	2.93	36	0.46	2.61
7	1.15	5.46	17	0.75	4.18	27	0.66	3.20	37	0.17	1.68
8	1.20	5.57	18	0.70	4.26	28	0.60	3.05	38	0.39	2.28
9	1.41	5.92	19	0.78	4.32	29	0.55	2.85	39	0.36	2.23
10	1.30	5.71	20	0.61	3.14	30	0.62	3.08	40	0.48	2.74
The Chinese A-Shares											
Lag(days)	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic
1	0.55	1.52	11	0.80	2.33	21	0.69	1.43	31	0.48	0.92
2	1.30	3.59	12	0.82	2.45	22	0.72	1.57	32	0.45	0.88
3	1.40	4.02	13	0.84	2.59	23	0.68	1.40	33	0.43	0.83
4	1.35	3.73	14	0.79	1.80	24	0.65	1.33	34	0.40	0.79
5	1.22	3.45	15	0.75	1.69	25	0.62	1.21	35	0.36	0.71
6	1.32	3.67	16	0.77	1.74	26	0.58	1.17	36	0.31	0.63
7	1.25	3.50	17	0.74	1.63	27	0.57	1.13	37	0.32	0.65
8	1.21	3.38	18	0.73	1.60	28	0.55	1.09	38	0.25	0.49
9	1.17	3.26	19	0.70	1.52	29	0.52	1.01	39	0.22	0.44
10	1.18	3.30	20	0.71	1.56	30	0.50	0.95	40	0.18	0.40

(Continued)

Table 1.10 – Continued

The Chinese B-Shares											
Lag(days)	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic
1	2.36	7.12	11	1.11	3.20	21	1.09	3.11	31	0.85	2.86
2	1.75	5.69	12	1.17	3.42	22	1.02	3.02	32	0.88	2.92
3	1.65	5.14	13	0.94	3.05	23	1.11	3.20	33	0.98	3.23
4	1.55	4.86	14	1.16	3.36	24	1.32	4.26	34	1.08	3.12
5	1.46	4.78	15	1.29	3.64	25	1.08	3.14	35	1.03	3.09
6	1.54	4.80	16	0.97	3.19	26	1.15	3.31	36	0.75	2.63
7	1.58	4.90	17	1.13	3.34	27	0.95	3.12	37	0.80	2.76
8	1.41	4.69	18	1.20	3.49	28	1.42	4.75	38	0.68	2.43
9	1.44	4.73	19	1.15	3.36	29	1.21	3.52	39	0.74	2.55
10	1.38	4.40	20	1.23	3.57	30	1.18	3.46	40	0.70	2.50
The Chinese H-Shares											
Lag(days)	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic	Lag	Return	t-Statistic
1	3.54	10.95	11	1.19	4.22	21	1.00	3.36	31	0.87	2.95
2	2.29	7.81	12	1.15	4.16	22	0.99	3.26	32	0.85	2.89
3	1.73	5.26	13	1.09	3.93	23	1.01	3.40	33	0.90	3.04
4	1.55	5.04	14	1.11	4.00	24	0.96	3.24	34	0.86	2.93
5	1.50	4.93	15	1.08	3.64	25	0.94	3.19	35	0.84	2.81
6	1.43	4.77	16	1.02	3.51	26	0.92	3.11	36	0.79	2.61
7	1.40	4.69	17	1.03	3.54	27	0.90	3.08	37	0.80	2.65
8	1.38	4.69	18	1.01	3.44	28	0.89	3.06	38	0.75	2.56
9	1.34	4.73	19	0.95	3.21	29	0.91	3.09	39	0.74	2.49
10	1.28	4.40	20	0.93	3.177	30	0.88	3.00	40	0.72	2.41

Table 1.11 : Index Inclusion and Institutional Holdings

This table reports the percentage of institutional holdings, percentage of float held by institutional investors, number of financial institutions holding/trading the shares and the percentage held by domestic investors. These measures are reported for the shares before the inclusion of 232 large cap A-shares in the MSCI Emerging Markets Index as of May 31, 2018 (before inclusion) and as of 1st March, 2019 (after inclusion).

Type	Number of Stocks	Institutional Holdings (Percentage)	Float held (Percentage)	Number of Institutions	Domestic Ownership (Percentage)
A-shares	232	49 (55)	18 (29)	100 (150)	85 (83)

Table 1.12 : Impact of Index Inclusion

This table reports the results for the simple cross-sectional regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{i,t-k} + \epsilon_{i,t}$, where t is the collection of all half-hour intervals for which the stock trades during the sample period split in to two parts-before and after the inclusion in the MSCI Emerging Markets Index (ranging from June 1, 2016 to May 31, 2018 and from June 1, 2018 to March 1, 2019 respectively). This sub-sample contains the 234 A-shares that were included in the MSCI Emerging Markets Index from June 1, 2018. $R_{i,t}$ is the return on the stock of firm i in interval t and $R_{i,t-k}$ is the return on the stock of firm i lagged by k intervals. The trading day is divided in to non-overlapping half-hour intervals, since the Chinese stock exchange operates from 9:30 to 11:30 am and then from 1:00 to 3:00 pm, we have 8 half-hour trading intervals each day. Stocks are sorted in to top and bottom deciles at the end of every half hour interval based on returns and the top and bottom deciles are dropped. The cross-sectional regressions are estimated for all half-hour intervals in the time sample for lags $k=8, 16, 34, 96$ and so on until 320 lags. These lags correspond to daily lags of 1,2,3,... 40 days. The time series averages of $\beta_{i,t}$ are reported in percentages as in [Heston, Korajczyk, and Sadka \(2010\)](#). Also, the corresponding Fama and Macbeth (1973) t-statistics are reported along side. This table separates our all A-share sample in to small, medium and large stocks by market capitalization to study the impact of size on the existence of the pattern. In the second row below the raw regression estimates the standardized estimates are also reported.

232 A- Shares-Before Inclusion

Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	0.76	4.89	21 Days	0.44	3.09
	0.46			0.26	
2 Days	0.83	5.74	22 Days	0.43	3.05
	0.48			0.25	
3 Days	0.86	5.93	23 Days	0.45	3.20
	0.51			0.27	
4 Days	0.72	4.52	24 Days	0.49	3.34
	0.37			0.29	
5 Days	0.70	4.23	25 Days	0.40	2.92
	0.41			0.23	
6 Days	0.71	4.32	26 Days	0.44	3.01
	0.41			0.25	
7 Days	0.65	4.12	27 Days	0.41	2.95
	0.39			0.24	
8 Days	0.67	4.19	28 Days	0.48	3.25
	0.40			0.29	
9 Days	0.63	4.08	29 Days	0.42	3.01
	0.38			0.25	
10 Days	0.60	3.86	30 Days	0.35	2.78
	0.36			0.21	
11 Days	0.63	4.01	31 Days	0.32	2.65
	0.38			0.19	
12 Days	0.62	3.92	32 Days	0.33	2.69
	0.37			0.20	
13 Days	0.60	3.79	33 Days	0.30	2.43
	0.36			0.18	
14 Days	0.54	3.52	34 Days	0.29	2.37
	0.32			0.17	
15 Days	0.55	3.56	35 Days	0.31	2.52
	0.33			0.19	
16 Days	0.50	3.35	36 Days	0.30	2.41
	0.30			0.18	
17 Days	0.57	3.65	37 Days	0.27	2.31
	0.34			0.16	
18 Days	0.54	3.49	38 Days	0.28	2.34
	0.32			0.17	
19 Days	0.52	3.43	39 Days	0.26	2.26
	0.31			0.16	
20 Days	0.51	3.40	40 Days	0.24	2.19
	0.31			0.14	

(Continued)

Table 1.12 – *Continued*

232 A- Shares-After Inclusion					
Lag	Estimate	t-Statistic	Lag	Estimate	t-Statistic
1 Day	1.68	9.25	21 Days	1.22	3.45
	0.81			0.64	
2 Days	1.51	6.87	22 Days	1.25	3.69
	0.75			0.65	
3 Days	1.45	6.26	23 Days	1.23	3.55
	0.72			0.65	
4 Days	1.40	5.22	24 Days	1.25	3.65
	0.69			0.65	
5 Days	1.38	4.98	25 Days	1.26	3.80
	0.68			0.66	
6 Days	1.35	4.72	26 Days	1.22	3.43
	0.68			0.64	
7 Days	1.32	4.36	27 Days	1.28	4.02
	0.67			0.66	
8 Days	1.33	4.44	28 Days	1.20	3.34
	0.65			0.63	
9 Days	1.35	4.70	29 Days	1.21	3.39
	0.65			0.62	
10 Days	1.31	4.29	30 Days	1.19	3.27
	0.64			0.61	
11 Days	1.32	4.34	31 Days	1.22	3.39
	0.65			0.63	
12 Days	1.29	4.06	32 Days	1.20	3.33
	0.64			0.61	
13 Days	1.30	4.12	33 Days	1.18	3.20
	0.65			0.59	
14 Days	1.31	4.27	34 Days	1.16	3.02
	0.65			0.58	
15 Days	1.28	3.94	35 Days	1.17	3.11
	0.64			0.59	
16 Days	1.30	4.08	36 Days	1.20	3.29
	0.65			0.61	
17 Days	1.25	3.72	37 Days	1.24	3.57
	0.63			0.62	
18 Days	1.26	3.81	38 Days	1.20	3.26
	0.63			0.60	
19 Days	1.23	3.59	39 Days	1.18	3.39
	0.62			0.59	
20 Days	1.25	3.68	40 Days	1.17	3.05
	0.62			0.58	

Table 1.13 : High Minus Low Portfolio Returns After Index Inclusion

This table reports the performance for the portfolios formed on the basis of each half-hour interval's returns. The stocks are sorted every half hour and portfolios are formed using the top and bottom deciles and their half hour returns are observed for the next forty days(during the same half hour interval). All intervals from 8:00 to 16:30 are taken and stocks are sorted every half-hour. The sample contains 232 A-shares which were subject to inclusion in MSCI Emerging Markets Index inclusion from the period ranging from June 1, 2016 to May 31, 2018 (before inclusion in MSCI Emerging Markets Index) and from June 1, 2018 to March 1, 2019 (after inclusion in the MSCI Emerging Markets Index). The average return spreads(top minus bottom decile) on portfolios formed on the basis on the performance during the relevant historical half hour (with lags 1 to 40 days) interval are reported. The stocks are grouped in to ten portfolios with an equal number of stocks in each portfolio. The returns are reported in basis points.

232 A- Shares–Before Inclusion

Lag	Returns	t-Statistic	Lag	Returns	t-Statistic
1 Day	1.44	4.38	21 Days	0.93	3.19
2 Days	1.52	4.46	22 Days	0.91	3.14
3 Days	1.58	4.61	23 Days	0.88	3.09
4 Days	1.30	4.24	24 Days	0.90	3.12
5 Days	1.21	4.06	25 Days	0.85	2.92
6 Days	1.16	3.98	26 Days	0.81	2.81
7 Days	1.11	3.88	27 Days	0.82	2.85
8 Days	1.09	3.74	28 Days	0.79	2.75
9 Days	1.10	3.77	29 Days	0.80	2.77
10 Days	1.05	3.61	30 Days	0.79	2.72
11 Days	1.02	3.55	31 Days	0.75	2.65
12 Days	1.04	3.56	32 Days	0.72	2.55
13 Days	1.02	3.42	33 Days	0.70	2.50
14 Days	1.01	3.34	34 Days	0.68	2.45
15 Days	0.98	3.26	35 Days	0.65	2.38
16 Days	0.95	3.19	36 Days	0.66	2.41
17 Days	0.96	3.21	37 Days	0.62	2.33
18 Days	0.93	3.12	38 Days	0.56	2.24
19 Days	1.00	3.36	39 Days	0.60	2.30
20 Days	1.04	3.51	40 Days	0.55	2.19

232 A- Shares–After Inclusion

Lag	Returns	t-Statistic	Lag	Returns	t-Statistic
1 Day	2.85	8.85	21 Days	1.26	4.80
2 Days	2.30	7.74	22 Days	1.29	4.87
3 Days	2.15	7.51	23 Days	1.20	4.63
4 Days	2.09	7.35	24 Days	1.22	4.69
5 Days	2.01	7.05	25 Days	1.25	4.75
6 Days	1.95	6.85	26 Days	1.17	4.52
7 Days	2.00	6.92	27 Days	1.11	4.36
8 Days	1.94	6.81	28 Days	1.13	4.42
9 Days	1.90	6.69	29 Days	1.08	4.21
10 Days	1.88	6.61	30 Days	1.11	4.30
11 Days	1.75	6.22	31 Days	1.02	4.10
12 Days	1.65	5.95	32 Days	1.04	4.12
13 Days	1.60	5.84	33 Days	0.95	3.95
14 Days	1.52	5.62	34 Days	0.91	3.74
15 Days	1.45	5.47	35 Days	0.87	3.58
16 Days	1.40	5.35	36 Days	0.74	3.33
17 Days	1.36	5.23	37 Days	0.70	3.26
18 Days	1.38	5.29	38 Days	0.62	3.15
19 Days	1.35	5.12	39 Days	0.65	3.20
20 Days	1.30	4.95	40 Days	0.60	3.04

Chapter 2

Market Efficiency and the Impact of Limits of Arbitrage, Regulations and Index Inclusion: Intraday Evidence from a Large Sample of Chinese Stocks

“The Chinese stock market is still in the initial stage of development and the total market capitalization is becoming bigger and bigger, but the quality of the stock market still has some problems (such as) the transparency, the supervision, the maturity of the investors and whether they know what they are doing.”¹

(Zhou Xiaochuan, Former Governor, People’s Bank of China.)

“Early on in the development of markets there’s probably some tendency for them I think to be more speculative than markets that have been around for a couple hundred years. Markets have a casino characteristic that has a lot of appeal to people, particularly when they see people getting rich around them. And those who haven’t been through cycles before are more prone to speculate than people who have experienced the outcome of wild speculation.”²

(Warren Buffett, CEO, Berkshire Hathaway.)

¹See the interview available on CNBC <https://www.cnbc.com/2018/09/11/chinas-stock-market-is-still-immature-so-volatility-is-to-be-expected-former-pboc-governor-says.html>

²See the interview available on CNBC <https://www.cnbc.com/2017/05/06/buffett-warns-china-that-markets-can-sometimes-become-a-casino.html>

2.1 Introduction

While the Chinese market is the second largest stock market in the world after the United States, it is still often referred to as a ‘casino’.³ Despite this negative publicity recent data shows that northbound flow of funds from Hong Kong to mainland China on the Shanghai and Shenzhen stock exchanges from foreign investors in early 2018 has reached roughly 10 billion RMB per month on each of the exchanges up from just around 5 billion RMB per month in early 2017 through the Stock connect program.⁴ Carpenter, Lu, and Whitelaw (2015) state that China’s stock market reputation as a ‘casino’ is ill founded. They claim that the price informativeness of the Chinese stock market in terms of fundamentals being reflected in prices is now comparable to that of the US.

The Chinese market is principally different in terms of investor composition⁵, market micro-structure⁶, trading constraints⁷ and regulatory framework⁸ from the US markets. These factors have been blamed for its ‘casino’ like behaviour. Most of the criticism comes due to its investor composition which is primarily constituted of retail domestic investors(see Pan, Tang, and Xu (2015), Kong, Lin, and Liu (2017)).

Some studies in the past have attempted to study intraday market efficiency in China, but they have mostly considered a small sample of firms, used only one traditional measure of efficiency and have focused on time periods up to 2010.⁹ In a rapidly changing market such as China which has undergone some major reforms since 2010 and has grown considerably in size and in terms of the number of firms that are listed on Chinese exchanges and

³An article in the Economist is titled ‘A crazy casino’ referring to China’s stock market. See : <https://www.economist.com/free-exchange/2015/05/26/a-crazy-casino> and an article published in Forbes which suggests that retail investors hold as much as 80 percent of the Chinese equities and ‘play’ the Chinese stock market like a casino. See : <https://www.forbes.com/sites/peterpham/2018/02/22/what-is-the-value-of-chinas-stock-market/>

⁴An article in the Financial Times provides this data. See : <https://www.ft.com/content/093117e6-898b-11e8-bf9e-8771d5404543>

⁵The Chinese market has various share classes A-shares(dominated by domestic retail investors), B-shares(dominated by foreign investors) and H-shares(listed outside mainland China in Hong Kong.

⁶The Chinese market is more centralized whereas the US market is fragmented with multiple trading venues. This has various implications for price informativeness (Carpenter, Lu, and Whitelaw (2015)).

⁷The Chinese market imposes restrictions in terms of price limits of ten percent on each trading day and the day trading rule which requires a minimum holding period of one day.

⁸For instance, the maximum trading day gain is capped at 44 percent for stocks that debut during the IPO. This has lead to a drop in IPO listings and companies such as Xiaomi Corp. chose listing in Hong Kong instead. See : <https://www.bloomberg.com/opinion/articles/2019-01-28/china-s-csrc-change-signals-easing-stock-regulation>

⁹Studies such as Narayan, Narayan, and Westerlund (2015) study the predictability of stock returns based on past intraday order imbalances for 330 stocks listed on the Shenzhen and Shanghai stock exchanges from 2008-2010.

also experienced the launching of new trading exchanges, new evidence is warranted. For instance the ChiNext¹⁰ which was launched in the end of 2009 today alone has more than 800 stocks listed on it and acts as a testament to the need of studying market efficiency using a large sample of Chinese stocks and for the most recent period.

We wish to conduct a comprehensive test of intraday market efficiency in Chinese stock markets based on a large sample of stocks, using two widely used traditional measures of market efficiency and for the most recent time period. Our first measure of intraday market efficiency is based on the seminal study of Chordia, Roll, and Subrahmanyam (2005) who device an effective way to determine the speed of convergence to market efficiency. They measure the speed as the time taken by the markets to remove all predictability of returns by either past returns (weak form efficiency) or from past short term interval order flows (strong form efficiency). This approach is a simple approach and has come to be used extensively by studies interested in investigating the speed of convergence to market efficiency (see Röscher, Subrahmanyam, and Van Dijk (2016), Carrion (2013), Chung and Hrazdil (2012), Visaltanachoti and Yang (2010), Chung and Hrazdil (2010), Chordia, Roll, and Subrahmanyam (2008)).

Furthermore, we will test intraday market efficiency and adherence to random walk by using the variance ratio tests as done by Röscher, Subrahmanyam, and Van Dijk (2016) for all New York Stock Exchange (NYSE) stocks. The Variance ratios are calculated as the ratio of thirty times the variance of the returns of one-minute intervals to the variance of the returns of the thirty-minute intervals for each stock. If prices follow a random walk this ratio should be close to unity. To further perform an in-depth analysis of intraday market efficiency patterns, we segregate the trading day in to 8 half hour intervals in exact multiples of 30 minutes from 9:30 - 10:00 am and so on and so forth. This will enable us to determine which half hour interval is the best time to trade in terms of market efficiency.

There are various limitations to our study-for instance we only use the return predictability framework adapted by Chordia, Roll, and Subrahmanyam (2005) using the short term predictive power of past returns and order imbalances. We only study very short intervals of up to ten minutes. Chordia, Roll, and Subrahmanyam (2005) make a statement demanding caution on interpreting the level of market efficiency using their framework as even though they document that markets become efficient over very short intervals of time, well known market anomalies which defy all principles of market efficiency still exist and encourage further study in to these as it would be interesting to know

¹⁰See: <https://dealbook.nytimes.com/2009/10/30/china-opens-nasdaq-like-exchange-in-shenzhen/>

the exact time and mechanism through which markets go from being efficient at very short intervals to exhibiting inefficiency at longer intervals. Moreover, the measures of market efficiency that we discuss here are only testing for weak to semi-strong form efficiency ((Fama, 1970)) which means that prices reflect publicly available information effectively. The original measures which were observable only by specialists in 2005 can now actually be calculated and deciphered by sophisticated algorithms in the age of algorithmic trading.

Also, we use a relatively short period of very recent data ranging from April 1, 2016 to April 1, 2019 which is not sufficient to make a valid and absolute claim regarding the long term market efficiency of stock markets in China. Our analyses is limited to two high frequency measures and rather than making a claim on the nature of market efficiency in China, we explore how recent developments such as relaxing the barriers to accessing stocks through the Shenzhen Stock Connect program and inclusion of stocks in the MSCI index impact the high frequency market efficiency measures. The study provides evidence that these steps have indeed improved market efficiency in terms of the the high frequency based market efficiency measures. Also, it provides an impetus for Chinese policy makers to keep taking steps to institutionalize the Chinese A-shares market as it is leading to improvement in market efficiency which is critical to raising capital and catalysing the high rate of growth necessary to provide opportunities to the Chinese public.

The other aspect that this study attempts to address is the presence of limits of arbitrage unique to China as explained in (Gu, Kang, and Xu, 2018). We show that these limits of arbitrage act as an impediment to achieving market efficiency as demonstrated by the high frequency market efficiency measures. Chinese policy makers must therefore, increase attempts to cautiously reduce these limits of arbitrage by striking a balance between their benefits and costs. Also, this study renders support to the argument that Chinese policy makers are already in the process of enabling the transformation of Chinese stock markets from an individual investor dominated market to a more mature market that will gradually come to be dominated by institutional investors and thereby make it more efficient.

Chordia, Roll, and Subrahmanyam (2008) show that higher liquidity facilitated by lower bid-ask spreads post decimalization in the United States was successful in lowering return predictability. Short term return predictability is eliminated more effectively when arbitrageurs are able to trade with greater ease and pay lower transaction costs (Chordia, Roll, and Subrahmanyam (2008)). Kadapakkam (2000) show that lowering limits of arbitrage by introducing electronic trading improved market efficiency in Hong Kong. Al-

though [Ljungqvist and Qian \(2016\)](#) show that over longer intervals ranging from 5 up to 60 days, arbitrageurs devise various strategies to overcome limits of arbitrage, yet there is no evidence that shows that limits of arbitrage over short term intraday intervals ranging from 1 minute to 10 minutes (which is our time frame of interest) can be overcome.

The Chinese market is subject to some trading constraints and regulations that do not exist in the United States. These unique trading regulations are laid out in particular detail by [Gu, Kang, and Xu \(2018\)](#) who classify them as limits of arbitrage. Of particular importance are the price limit rule and the day trading rule. According to the price limit rule, a trader cannot post limit orders to buy or sell a stock that is more than 10 percent higher or lower than the previous close. The price limit rule is likely to lead to a low probability of trade execution in the event of a price limit hit ([Gu, Kang, and Xu \(2018\)](#)).

There has been a great level of debate surrounding the impact of price limits. [Kim and Park \(2010\)](#) claim that price limits curb manipulation and thereby have a beneficial impact on the markets. [Deb, Kalem, and Marisetty \(2010\)](#) show that price limits have a beneficial impact in countries with high monitoring costs owing to high levels of corruption and a poor legal, regulatory and technological environment. [Li, Zheng, and Chen \(2014\)](#) show that price limits help curb volatility and trading activity during downward price limit hits, but upward price limit hits do not show any beneficial impact and they also show that price limits have no impact on price discovery in Chinese stocks. [Gu, Kang, and Xu \(2018\)](#) find that trading constraints actually hurt investors by causing high idiosyncratic volatility stocks with high limits of arbitrage to underperform creating market inefficiencies and that Chinese policy makers should reconsider enforcement of the unique trading constraints imposed by them. The impact of trading constraints on market efficiency in terms of traditional measures of market efficiency has not been studied in Chinese markets on an intraday or daily level before. We intend to fill this void by conducting a study of the impact of limits of arbitrage on market efficiency measured in terms of intraday return predictability and intraday variance ratios.

[Gu, Kang, and Xu \(2018\)](#) develop a Limits of Arbitrage index based on six barriers to arbitrage: (i) price limits (10 percent higher or lower than previous close) inhibit the probability of trade fulfilment and lead to higher limits of arbitrage once a price limit is hit in either direction, (ii) short selling constraints offer higher limits of arbitrage as not all stocks can be shorted under the current Marginal Trading and Short Selling (MTSS) program, (iii) inclusion in the China Securities Index 300 (CSI 300) which in turn enables arbitrageurs to engage in offsetting trades to minimise any potential adverse impact of

their trades by virtue of index futures contract, (iv) stock illiquidity which translates to higher transaction costs and decreases any potential gains that arbitrageurs can obtain from engaging in the correction of mispricing relative to fair value, (v) trading volumes can also act as a significant barrier to arbitrage activity as a thin market avoids smooth execution of an arbitrageurs attempt to remove any mispricing by providing an insufficient volume of stock available for execution of the strategy and having an adverse price impact on the stock ([Pagano \(1989\)](#)) which further discourages arbitrage activity and (vi) analyst coverage provides an impetus to arbitrageurs to act collectively to mitigate any mispricing.

Following the methodology of [Gu, Kang, and Xu \(2018\)](#) we formulate a Limits of Arbitrage Index as well and classify our stocks in to five categories. The Limits of Arbitrage Index reading ranges from 0.00 to 1.00, the five groups range from 0.00-0.20, 0.21-0.40, 0.41-0.60, 0.61-0.80, 0.81-1.00. The lower the Index reading, the lower the limits of arbitrage. Our findings indicate that higher limits of arbitrage lead to greater inefficiency in the markets as suggested by both the traditional measures of market efficiency that we consider.

The unique features of China's capital markets with the existence of A, B and H shares and trading constraints which impose limits of arbitrage are being exploited heavily to study various known and unknown phenomenons. [Li, Brockman, and Zurbruegg \(2015\)](#) study the incorporation of information in to prices by studying A- shares and H- shares and find that the ability of foreign investors to utilize firm specific information and incorporate it in to prices is one of the implicit benefits of cross-listing. [Gu, Kang, and Xu \(2018\)](#) find that the trading constraints such as price limits and short selling constraints which translate to additional limits of arbitrage have a negative impact on market efficiency. [Chui and Titman \(2017b\)](#) go as far as calling the segmented Chinese market with A and B-shares as 'ideal laboratory' for studying the varying impacts of investor composition on the momentum effect.

[Upson and Van Ness \(2017\)](#) find that the U-shaped pattern in intraday bid-ask spreads is actually an S-shaped pattern. We investigate the intraday pattern of bid-ask spreads in Chinese markets and find that the bid-ask spread is highest in the first half hour of trading and then experiences a monotonous decrease until lunch time. After the lunch break, when trading resumes there is another increase in the bid-ask spread followed by a steady decline until closing. Since transaction costs are a commonly recognized limit of arbitrage, we test for a time of the day effect in market efficiency by conducting our variance ratio analysis for 8 half hour intervals of the trading day. Our results confirm

that in the opening half hour interval in the morning and post lunch when the transaction costs offer higher limits of arbitrage relative to other half hour intervals, the variance ratio deviate from unity and imply non-adherence to random walk.

We consider a very recent time period to study intraday market efficiency in Chinese markets because we intend to study the impact of three landmark events namely- (1) The opening up of Shenzhen stock exchange's A-shares to foreign investors through the Shenzhen stock connect program (initiated in December, 2016). (2) The second was the inclusion of 232 A-shares in the Morgan Stanley Capital Index for emerging markets (included in June, 2018). The impact of these two major events will be studied under the event study methodology employed by [Chang, Luo, and Ren \(2014\)](#) who study the impact of the Marginal Trading and Short Selling (MTSS) program introduced in 2010 on market efficiency. [Chang, Luo, and Ren \(2014\)](#) impose a pre-event and a post-event window in which they drop the 31 days prior to the implementation in the pre-event window and 31 days after the introduction of the change for studying the impact post event. This exclusion of 31 days from the pre-event and post-event window is also in line with studies such as [Amihud, Mendelson, and Lauterbach \(1997\)](#) and [Chang, Cheng, and Yu \(2007\)](#). Also, in line with [Chang, Cheng, and Yu \(2007\)](#) we employ a requirement whereby, the minimum period of study is 180 days in each estimation window.

However, since we are looking at intraday trading intervals our measures will continue to be the intraday return predictability measure and intraday variance ratios. The Shenzhen stock connect program which included 881 stocks and the inclusion of the 232 A-shares in the MSCI index both would lead to an increase in trading volume of the included stocks and that would in turn increase the trading volume on these stocks, thereby lowering limits of arbitrage. These two event studies provide an ideal setting to further study the impact of limits of arbitrage on market efficiency in China under the premise of a natural experiment. Our findings indicate that during the post event window of both these events, market efficiency improved across both our measures of market efficiency. The remainder of this paper is organized as follows: Section 2 discusses the data and methodology. Section 3 discusses the empirical findings and Section 4 concludes the paper.

2.2 Data and Methodology

This study utilizes data from two databases. The high frequency trade and quote tick data for quotes (bids and asks) and trades is collected from Bloomberg. This data is

then filtered for all A-shares using the firm classification data collected from The China Stock Market and Accounting Research database (CSMAR) database. We only keep common stocks of A-shares and our final sample contains 3473 A-shares for the time period between April 1, 2016 to April 1, 2019. We make use of the equity screening function in Bloomberg to generate lists in the Bloomberg environment which are then recalled using the Bloomberg-Excel interface to download the data.

Table 2.1 presents an overview of the Chinese A-shares included in our sample. There are 1344 A-shares listed in Shanghai in our sample and 2129 A-shares listed across all boards on the Shenzhen exchange that are there in our sample. The mean market capitalization of the stocks listed in Shanghai is 18.75 (billions of RMB) and the mean market capitalization of the stocks listed in Shenzhen is 10.15 (billion of RMB). Therefore, on average bigger firms are listed on Shanghai than there are in Shenzhen. Also, the break down of Shenzhen stocks across its three boards is as follows- 463 A-shares on the Main Board, 921 A-shares on the SME Board and 745 A-shares on the youngest board which is a NASDAQ style board dedicated to technology and IT stocks the ChiNext.

Using the methodology of Chordia, Roll, and Subrahmanyam (2008) we match trades to quotes which occur immediately prior to the occurrence of the trade. We discard any quotes which give a negative bid-ask spread, any trades that have a negative or zero volume and any trades that occur outside regular trading hours. This allows us to avoid our results being driven by any spurious observations.

To avoid the bid-ask bounce and non synchronous trading we use mid-point quote returns instead of using trade returns. This is in line with studies such as Röscher, Subrahmanyam, and Van Dijk (2016). Order imbalances are calculated using the Lee and Ready (1991) algorithm which enables us to sign trades effectively. It is among the most reliable algorithms used to determine trade direction and has been used by several past studies (see Röscher, Subrahmanyam, and Van Dijk (2016), Chordia, Roll, and Subrahmanyam (2008)).

2.2.1 Description of Variables

Variable 1 Returns : *These returns are mid-quote returns which are calculated using the midpoint quotes at the end and the beginning of the trading intervals of lengths 1 minute, 2 minutes, 5 minutes, 10 minutes and 15 minutes. For example, Returns are calculated for the 5 minute interval from 9:45-9:50 using the midpoint of the first and last quotes from the interval 9:45:00-9:50:00. This methodology for calculating returns is consistent with Röscher, Subrahmanyam, and Van Dijk (2016) and Chordia, Roll, and Subrahmanyam (2005).*

Returns = (Midpointquote_{last} - Midpointquote_{first})/Midpointquote_{first}
where, Midpointquote_{last(first)} = (Bid_{last(first)} + Ask_{last(first)})/2

Variable 2 OINUM : This measure of order imbalance is computed by taking the net difference of the number of buyer initiated trades versus seller initiated trades. [Lee and Ready \(1991\)](#) algorithm is used to sign the trades and designate trades as either initiated by buyers or sellers. This is consistent with both [Chordia, Green, and Kottimukkahur \(2018\)](#) and [Chordia, Roll, and Subrahmanyam \(2008\)](#).

$$OINUM = (\text{Buyer initiated trades} - \text{Seller initiated trades}) / \text{Total number of trades}.$$

Variable 3 OIVAL: This measure of order imbalance is computed by taking the net difference of the value of the buyer initiated trades versus the seller initiated trades. This measure takes in to regard the size and the value of the trades versus just taking the difference in terms of the number of trades as in OINUM. This definition is consistent with [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#).

$$OIVAL = \text{Value of buyer initiated trades} - \text{Value of seller initiated trades}$$

2.2.2 Intraday Return Predictability

Table 2.2 provides a summary statistics of the key variables that will be used to determine the intraday return predictability measure. The measures of short term mid quote returns and order imbalances are consistent and comparable with recent studies such as [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) that use these variables to determine intraday return predictability measure.

Our first measure of market efficiency is based on the framework pioneered by [Chordia, Roll, and Subrahmanyam \(2005\)](#) who use the time taken to remove intraday return predictability of lagged returns and lagged order imbalances (in a univariate framework) or their combination (in a multivariate framework) to measure market efficiency. This framework was most recently used by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#). We use intervals of 1 minute, 2 minutes, 3 minutes, 5 minutes and upto 10 minutes.

We begin by demonstrating a univariate framework which can be used to test for the weak form efficiency. Weak form efficiency in this framework pertains to the time taken to remove any predictability of returns in a current intraday interval based on returns in the past interval of the same length. Equation 2.1 is based on the principle of weak form efficiency as laid out by [Fama \(1970\)](#) which states that any publicly available past information should not be a predictor of future returns.

This is then followed by a test of semi-strong form efficiency to see how long it takes for order imbalances to lose their predictive power in predicting future returns. [Bailey, Cai, Cheung, and Wang \(2009\)](#) show that on a daily basis order imbalances from individual investors explain a significant amount of price fluctuations, the sample period extends from October 2003 to March 2004 for a total of 117 days, for 198 stocks traded on the Shanghai Stock Exchange. A univariate framework can now be used to regress the stock returns for the current time interval on lagged order imbalances in the interval immediately preceding

the current interval. We use two different measures of order imbalance as also used by [Chordia, Roll, and Subrahmanyam \(2005\)](#). The regression will be based on individual stock regressions and the cross sectional mean of all the regressions will be reported. We use two distinct measures of order imbalances as defined in variable definition [2](#) and [3](#).

$$Returns_{i,t} = \alpha_{i,t} + \beta_{i,t}Returns_{i,t-1} + \epsilon_{i,t} \quad (2.1)$$

$$Returns_{i,t} = \alpha_{i,t} + \beta_{i,t}OINUM_{i,t-1} + \epsilon_{i,t} \quad (2.2)$$

$$Returns_{i,t} = \alpha_{i,t} + \beta_{i,t}OIVAL_{i,t-1} + \epsilon_{i,t} \quad (2.3)$$

For our analyses, we adapt a more robust multivariate framework where we regress current interval's returns ($Returns_{i,t}$) on the immediately preceding interval's returns ($Returns_{i,t-1}$) and the immediately preceding interval's order imbalance ($OINUM_{i,t-1}$) as shown in regression equation [2.4](#). In regression equation [2.5](#) we change the regression specification and replace ($OINUM_{i,t-1}$) with ($OIVAL_{i,t-1}$) as the independent variable to study the intraday return predictability.

$$Returns_{i,t} = \alpha_{i,t} + \beta_{1,t}Returns_{i,t-1} + \beta_{2,t}OINUM_{i,t-1} + \epsilon_{i,t} \quad (2.4)$$

$$Returns_{i,t} = \alpha_{i,t} + \beta_{1,t}Returns_{i,t-1} + \beta_{2,t}OIVAL_{i,t-1} + \epsilon_{i,t} \quad (2.5)$$

Where $Returns_{i,t}$ is the mid quote return associated with stock i during the interval t calculated as per the definition of Variable [1](#). $OINUM_{i,t-1}$ is the lagged order imbalance of $OINUM_{i,t-1}$ (calculated as per the definition of Variable [2](#) associated with stock i during the preceding time interval $t - 1$. $OIVAL_{i,t-1}$ is the $OIVAL$ (calculated as per the definition of Variable [3](#))associated with stock i over the immediately preceding time interval $t - 1$. For equations 2.1-2.5, the smaller the coefficients β , β_1 , β_2 the smaller the amount of return predictability and hence the greater the amount of efficiency.

Consistent with the framework of [Chordia, Roll, and Subrahmanyam \(2005\)](#), a separate regression is run for each A-share. The cross sectional mean of the coefficients each A-share is the coefficient of interest. The statistical significance is measured in terms to the t-statistic which is obtained by taking the cross sectional mean of t-statistics for each A-share. We also report a second t-statistic which is the more reliable t-statistic and is based on a technique pioneered by [Chordia and Swaminathan \(2000\)](#). This technique adjusts

the first t-statistic for any cross correlation in residuals and is calculated by scaling the standard error by a factor of $\sqrt{1 + (N - 1)\rho}$, where $N=3473$ is the number of A-shares. ρ is obtained by estimating the average of the pair wise cross correlation of adjacent stocks and in this case we will have 6,029,128 pairwise correlations for the residuals of the 3473 individual A-share regressions.

2.2.3 Variance Ratios

We use the framework of [Lo and MacKinlay \(1988\)](#) which has been widely in recent studies (see [Conrad, Wahal, and Xiang \(2015\)](#), [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#)) to calculate the variance ratio measures of intraday market efficiency. Following [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) we consider the ratios of the variances of 1 minute returns to the variance of 30 minute returns, over each half hour trading interval of measurement during the day. The variance ratio is interpreted as a measure of serial dependence in stock returns and as the ratio converges to one, serial dependence is interpreted as converging to zero ([Rösch, Subrahmanyam, and Van Dijk \(2016\)](#)) and adherence to random walk is hence strengthened. As a robustness check, we also consider the ratios of the variances of 15 seconds returns to the variance of 5 minute returns, also over each half hour trading interval of measurement during the day which is in line with [Conrad, Wahal, and Xiang \(2015\)](#).

Our choice of the measurement interval as 30 minutes is based on the reasoning that the interval needs to be long enough to capture any significant differences in the variances of short and long horizon returns within that interval while preserving the time of the day effects [Conrad, Wahal, and Xiang \(2015\)](#). Also studies such as [Heston, Korajczyk, and Sadka \(2010\)](#) and [Gao, Han, Li, and Zhou \(2018\)](#) attach great importance to half hour intervals as they capture significant time of the day effects and account for phenomenon of material importance in the financial markets.

In line with the framework of [Lo and MacKinlay \(1988\)](#) as also adapted by [Conrad, Wahal, and Xiang \(2015\)](#), we say that $\tau = sL$. L is the number of longer horizon intervals(i.e. number of 15 minute and 30 minute returns) in our interval of measurement which is half an hour in both cases and s is the number of small horizon intervals in the longer horizon interval. Our interval of measurement is 30 minutes, and our long term intervals are 5 minutes and 30 minutes, therefore, $L = 6$ and $L = 1$ respectively. Our short horizon intervals are 15 seconds and 1 minute long respectively, therefore, $s= 20$ (number of 15 second intervals in 15 minutes) and $s=30$ (number of one minute intervals in 30 minutes)

respectively. Also, it is worthy to note that the short and long horizon intervals within each measurement interval of 30 minutes are non-overlapping intervals.

In the spirit of studies such as [Lo and MacKinlay \(1988\)](#) and ([Conrad, Wahal, and Xiang \(2015\)](#), [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#)) we define Q_t as a log price process, where $Q_t = Q_0, Q_1, Q_2, \dots, Q_\tau$, we would like to highlight that instead of using trade prices which are prone to bid-ask bounce and subject to non-synchronous trading, we use midpoint quotes. The variance ratios can be noisy and hence to minimise the affect of noise are calculated using overlapping returns ([Rösch, Subrahmanyam, and Van Dijk \(2016\)](#)).

The mean of midpoint quote returns is estimated by the following equation:

$$\hat{\mu} = \frac{1}{sL} \sum_{n=1}^{sL} (Q_n - Q_{n-1}) = \frac{1}{sL} (Q_{sL} - Q_0) \quad (2.6)$$

The Variance for the short term interval is calculated as per the following equation:

$$\text{Var}_{\hat{\text{short}}}[s] = \frac{1}{sL} \sum_{n=1}^{sL} (Q_n - Q_{n-1} - \hat{\mu})^2 \quad (2.7)$$

The Variance for the longer term interval is calculated as per the following equation:

$$\text{Var}_{\hat{\text{long}}}[s] = \frac{1}{s^2L} \sum_{n=s}^{sL} (Q_n - Q_{n-s} - s\hat{\mu})^2 \quad (2.8)$$

[Conrad, Wahal, and Xiang \(2015\)](#) follow the bias correction undertaken by [Lo and MacKinlay \(1988\)](#) and further refine the variance equations as:

$$\text{Var}_{\hat{\text{short}}}[s] = \frac{1}{sL - 1} \sum_{n=1}^{sL} (Q_n - Q_{n-1} - \hat{\mu})^2 \quad (2.9)$$

$$\text{Var}_{\hat{\text{long}}}[s] = \frac{1}{c} \sum_{n=s}^{sL} (Q_n - Q_{n-s} - s\hat{\mu})^2 \quad (2.10)$$

$$c = s(sL - s + 1) \left(1 - \frac{s}{sL}\right).$$

The Variance ratio is then defined as:

$$\frac{\text{Var}_{\hat{\text{long}}}[s]}{\text{Var}_{\hat{\text{short}}}[s]} \quad (2.11)$$

This ratio should converge to unity as the market's adherence to random walk increases. The ratio's convergence to unity implies that variances of the long term horizon and the shorter horizon within the measurement interval are linear ([Conrad, Wahal, and Xiang](#)

(2015)). In our case, this implies that for random walk to prevail, $\text{Var}(30 \text{ minutes}) = 30 * \text{Var}(1 \text{ minute})$ and for the second variance ratio test, $\text{Var}(5 \text{ minutes}) = 20 * \text{Var}(15 \text{ seconds})$.

2.2.4 Limits of Arbitrage Index

We formulate our limits of arbitrage index based on the techniques adapted by [Gu, Kang, and Xu \(2018\)](#) and employ all six attributes employed by them to create the limits of arbitrage index. The six attributes are namely- (i) daily price limits, (ii) short selling constraints determined by inclusion in the Marginal Trading and Short Selling program (MTSS) which can impede arbitrage activity and increase inefficiency ([Stambaugh, Yu, and Yuan \(2015\)](#)), (iii) ability to hedge trades measured by inclusion in the China Securities Index 300 (CSI) as index futures are traded and arbitrageurs can take offsetting positions in the futures markets, (iv) stock illiquidity which is associated with greater difficulty encountered by arbitrageurs while trading against any mispricing ([Chordia, Roll, and Subrahmanyam \(2008\)](#)), (v) trading volume facilitates arbitrage and is included as an indicator in the limits of arbitrage index and (vi) analyst coverage is another measure used in computing the limits of arbitrage index since investors are known to be attracted by attention grabbing stocks that come to the limelight as a consequence of analyst coverage ([Barber and Odean \(2007\)](#)). Also, [Andrade, Bian, and Burch \(2013\)](#) have highlighted that Chinese investors follow analyst reports closely as analyst coverage leads to smaller bubbles in stocks covered.

The limits of arbitrage index is calculated by taking the average of the values of the six individual indicators outlined above and stocks are evaluated on a daily basis. The individual measures of limits of arbitrage have binomial values of either 0(low) or 1(high) limits of arbitrage. We make some necessary changes to the frequency of assignment of either 0 or 1 to each stock for each indicator measure of the limits of arbitrage index for each trading day to better account for the high frequency intraday data that we are working with. We will outline the details of the calculations and changes made to them on a case by case basis for all six indicators used for calculating the index.

Following the notation and definition of individual indicators of the limits of arbitrage index we provide the modified definitions(to account for usage of high frequency data) use to derive the limits of arbitrage index. (i) $LALIMIT_{i,t}$ is the measure that is assigned a value of 0 for the stock ' i ' for each day of month ' t ' if no price limit is hit (i.e. the stock doesn't move above or below 10 percent from the previous close) and is assigned 1, if it

hits the price limit. This is then re-evaluated on a monthly basis for each month in the sample. (ii) $LAMTSS_{i,t}$ is the measure that is assigned a value of 0 for the stock ‘ i ’ on day ‘ t ’ if the stock is included in the Marginal Trading and Short Selling (MTSS) program for the day or 1 otherwise. (iii) $LACSI_{i,t}$ is the measure that is assigned a value of 0 for the stock ‘ i ’ on day ‘ t ’ if the stock is included in the CSI 300 program for the day or 0 otherwise. (iv) $LAAMIHUD_{i,t}$ is a measure of illiquidity that is assigned a value of 0 if the log [Amihud \(2002\)](#) measure for stock ‘ i ’ is below the cross sectional median of the day ‘ t ’ and 1 if it is higher than the median value. (v) $LAVOL_{i,t}$ is a measure that is assigned a value of 0 if the daily volume measure for stock ‘ i ’ is below the cross sectional median of the day ‘ t ’ and 1 if it is higher than the cross sectional median value. (vi) $LACOV_{i,t}$ is a measure of analyst coverage that is assigned a value of 0 if the number of analysts covering stock ‘ i ’ is below the cross sectional median of the day ‘ t ’ and 1 if it is higher than the cross sectional median value. For variance ratios tests, we use the daily index level to cluster our stocks and analyse each index level group together.

However, for application in the Multivariate Regression Analyses we construct the index by taking the average of the daily index value for each stock for the entire sample period. This leaves us with 740 stocks in the lowest limits of arbitrage category with a value of 0.00 to 0.20. We see that in [Table 2.2](#) the distribution across all five groups with index values ranging from 0.00-0.20, 0.21-0.40, 0.41-0.60, 0.61-0.80 and 0.81-1.00 is roughly 20%. The highest number of stocks fall in the higher limits of arbitrage group with index value of 0.61-0.80 which has 886 stocks. The smallest group is the 0.41-0.60 index value group with 602 stocks and comprising 17.33% of the entire sample.

2.3 Empirical Results

2.3.1 Intraday Return Predictability Measure Using the Entire Sample

Our sample of stocks contains all stocks listed on the Shanghai and Shenzhen exchanges for the time period between 1st April, 2016 to 1st March, 2019. In [Table 2.4](#) we report regression results for the multivariate regression represented by [Equation 2.4](#). The regression results are reported for each 1 minute, 2 minute, 3 minute, 5 minute and 10 minute trading interval from 9:30 to 11:30 am and from 1:00 to 3:00 pm. [Equation 2.4](#) regresses the current interval’s mid-quote returns on the mid-quote returns in the past interval of

same length(for instance the current 1 minute interval's returns are regressed on the previous interval of 1 minute length), the lagged order imbalance measure during the past interval of same length(for example, the returns of the interval 9:49:00 am to 9:50:00 am are regressed on order imbalance measures obtained from the previous 1 minute interval 9:48:00 am to 9:49:00 am). For each 1 minute, 2 minute, 3 minute, 5 minute and 10 minute interval two different regressions for each measure of order imbalance as described in Definition 2 and Definition 3 are reported.

The regression coefficients for the regression of mid-quote returns on lagged mid-quote returns can be interpreted as an indicator of weak form efficiency based on the framework of Fama (1970). According to the framework of Fama (1970) the markets are weak form efficient if they effectively incorporate all publicly available information at any given point in time. Since past interval returns are readily observable by all market participants, a lower regression co-efficient for returns on lagged returns and a lower statistical significance as demonstrated by our twin measures of t-statistics (the cross sectional mean of t-statistic obtained from the individual stock regressions and the t-statistic obtained from adjusting the first t-statistic obtained for cross correlation in residuals)imply lower predictability of returns from lagged returns and hence greater weak form market efficiency.

The regression coefficients for lagged returns are negative until the ten minute intervals that we consider. This is consistent with the short term return reversal phenomenon commonly observed in markets over the short term horizon (see Chordia, Roll, and Subrahmanyam (2005)). Furthermore, we observe a monotonous decrease in the magnitude of the regression coefficient and also in statistical significance as demonstrated by the more accurate second t-statistic reported in the second row below the coefficient and is adjusted for cross correlation in residuals as described in detail in the methodology section. The highest coefficient is obtained for the one minute interval for the *OINUM* as the second explanatory variable regression and is -0.050 and has a t-statistic of -5.85 and a second t-statistic of -3.72 which is adjusted for cross correlation in residuals.

The coefficient of returns on lagged returns over the one minute interval is negative and significant for the one minute interval and continues to be negative and significant over the two minute interval as well. It goes on to be negative and significant for up to three minutes with the coefficient at -0.032 for the *OINUM* as the second explanatory variable regression (Equation 2.4) and -0.027 for the regression over the three minute interval with *OIVAL* as the second explanatory variable (Equation 2.5). The second t-statistic(adjusted for cross correlation in residuals) is significant for up to three minutes but

it is just barely above the 2.00 level and we notice that it becomes completely insignificant at the 5 minute interval for which the coefficients are -0.027 and -0.026 for regressions represented by (Equation 2.4) and (Equation 2.5) respectively and the second t-statistics (adjusted for cross correlation in residuals) are -1.10 and -1.07 respectively. This leads us to infer that the entire sample of 3473 Chinese stocks listed on both the Shanghai and Shenzhen stock exchanges attain weak form efficiency in just over 3 minutes and well under 5 minutes as indicated by the regression coefficients and t-statistics.

We now move on to the coefficients of the order imbalance measures. Also, following the framework of Fama (1970) we classify intraday return predictability arising from lagged order imbalance as an indicator of semi-strong form efficiency as this information can be deciphered by more sophisticated traders and institutional investors (Chordia, Roll, and Subrahmanyam (2005)). We witness a trend where the strongest coefficients for both the order imbalances experience the highest economic and statistical significance for the one minute interval which is consistent with markets taking some time to absorb order imbalances and clear. The regression coefficient for the lagged order imbalance measure *OINUM* is positive and significant until we finally reach the 10 minute interval when the coefficient is 0.32 and the second t-statistic(adjusted for cross correlation in residuals) is 1.39. The same coefficient and t-statistic measures in the 5 minute interval are 0.75 and 2.82 respectively. This leads us to conclude that using the order imbalance measure *OINUM* the market reaches semi-strong form efficiency in more than 5 minutes but under 10 minutes. These findings are consistent with Chordia, Roll, and Subrahmanyam (2005) who also conclude that the markets reach weak form efficiency sooner than semi-strong form efficiency. Also, our results are consistent with Röscher, Subrahmanyam, and Van Dijk (2016) who show that order imbalances have a positive and significant coefficient in intraday return predictability regression for intervals of up to two minutes.

The regression coefficient for the lagged order imbalance measure *OIVAL* is positive and significant until we finally reach the 10 minute interval when the coefficient is 0.67 and the second t-statistic(adjusted for cross correlation in residuals) is 1.69 which is insignificant as Chordia, Roll, and Subrahmanyam (2005) regard a t-statistic of 2.00 as a benchmark for significance. Therefore, we can conclude that for the ten minute interval order imbalance measure *OIVAL* is not a significant predictor of intraday returns. However, like the other measure of order imbalance *OIVAL* measure it has positive and significant coefficients for intraday return predictability regressions of up to 5 minutes in length. This is again consistent with the findings of studies such as Chordia, Roll, and

Subrahmanyam (2005), Chordia, Roll, and Subrahmanyam (2008) and Röscher, Subrahmanyam, and Van Dijk (2016) who find that both measures of order imbalance in terms of the number of trades and the traded value are good predictors of returns over short term horizons.

As rightly pointed out by previous studies such as Chordia, Roll, and Subrahmanyam (2005), Chordia, Roll, and Subrahmanyam (2008) and Röscher, Subrahmanyam, and Van Dijk (2016), the R_2 measure of the regressions is another indicator of the level of efficiency in the markets. Consistent with the view that over time the market resolves any potential inefficiencies that arise over the short term horizon, we observe that as the time interval of interest increases in length the R_2 measure becomes smaller. This shows that given a longer amount of time, arbitrageurs have a greater potential to engage in offsetting transactions to push the market towards efficiency (Chordia, Roll, and Subrahmanyam (2005)). Therefore, the speed of convergence to efficiency or the time taken to remove intraday return predictability is an effective measure of market efficiency as we see that it tends to improve over a relatively greater amount of time as we move from a one minute to ten minute time window.

2.3.2 Intraday Return Predictability Measure Based on the Limits of Arbitrage Index Groups

Our sample of stocks contains all stocks listed on the Shanghai and Shenzhen exchanges for the time period between 1st April, 2016 to 1st March, 2019. The stocks are divided into five groups based on the daily limits of arbitrage index measure obtained as per the specifications detailed in Section 2.4. Recall that the lowest limits of arbitrage index group is for stocks that have the lowest limits of arbitrage with an index value in the range of 0.00 to 0.20. Whereas, the rest of the four groups experience the same scale range in increments of 0.20. Therefore, they are 0.21 to 0.40, 0.41 to 0.60, 0.61 to 0.80 and finally 0.80 to 1.00. These values are calculated on a daily basis for the entire time period from 1st April, 2016 to 1st March, 2019. The average of these daily index values for each stock is then taken for the entire time period and the stock is assigned a particular limits of arbitrage index group. This is in line with the methodology of Chordia, Roll, and Subrahmanyam (2005) who split the sample of their 150 stocks into small, medium and large cap stocks based on market capitalisation in the beginning of the year to study the impact of size on market efficiency. We do the same but classify the stocks into sub limits of arbitrage index group based on the average of their daily index values for the entire sample of the study.

We use the multivariate framework to study intraday return predictability as used in Section 3.1 and predict the regressions as per Equation 2.4 and Equation 2.5. The only difference is that now we have segregated the sample in to five distinct groups based on the average daily values of their limits of arbitrage index. The results are reported in Table 2.5.

We begin by discussing the lowest limits of arbitrage index group with an average index values ranging from 0.00 to 0.20. This reading is recorded on average by 740 stocks. The first coefficient of interest is the coefficient of current interval's mid-quote returns on lagged returns. We observe that stocks in the lowest limits of arbitrage index category achieve weak form efficiency in under one minute as the coefficient over the one minute interval is negative but insignificant. Furthermore, we notice a monotonous decline in the strength of the coefficient as we move to longer intervals such as the two minute, three minute, five minute and ten minute intervals. The co-efficient on the two lagged order imbalance measures from the period just preceding the current interval and of equal size are positive and significant. The value of the *OINUM* coefficient is 0.88 and *OIVAL* coefficient is 2.21 (and these are multiplied by 10_6 and 10_9 respectively for presentation purposes). The values for the corresponding second t-statistic (adjusted for cross correlation in residuals) are 3.09 and 3.11 respectively. These values indicate that the stocks in this group are still semi-strong form inefficient over the 1 minute interval. As we move to the two minute interval, coefficients for both the order imbalance measures remain positive but turn insignificant with the second t-statistic recording a value of 1.84 for *OINUM* and 1.89 for *OIVAL* respectively. Since the coefficients were statistically significant at the one minute interval and turn insignificant for the two minute interval, we infer that the stocks in the lowest limits of arbitrage group take more than one minute but less than two minutes to become semi-strong form efficient. Also, as you across to larger intervals such as 3, 5 and 10 minute intervals, the coefficients on the lagged order imbalances experience declines both in the economic and statistical significance.

We then turn our attention to the second lowest limits of arbitrage index group. Unlike the lowest limits of arbitrage index group it can be seen that the coefficient on lagged returns in both regressions based on Equation 2.4 and Equation 2.5 are negative and significant until the two minute interval and remain negative but turn insignificant over the three minute interval. This finding is unique in the sense that it shows that as the limits of arbitrage index level rose and we moved from the group with an average value of 0.00 to 0.20 to the group with average index values of 0.21 to 0.40, the time taken

to achieve weak form efficiency increases from under one minute to over two minutes, but within three minutes. This provides the first proof of evidence that higher limits of arbitrage affect the market efficiency in an adverse way and inefficiencies last longer.

This evidence is further supported by the results obtained for the coefficients of regression on both lagged order imbalances as well. We notice that these coefficients have a positive and significant value until the three minute interval and remain positive but turn insignificant with coefficient values of 0.70 for *OINUM* and 0.82 for *OIVAL* with the second cross correlation adjusted t-statistic reading of 1.97 and 1.61 respectively and reported in the second row in parentheses below the coefficients in Table 2.5. These results further establish the impact of limits of arbitrage on market efficiency and show that higher limits of arbitrage are an impediment to market efficiency. These results are consistent with Chordia, Roll, and Subrahmanyam (2008) who find that liquidity impedes market efficiency. Our limits of arbitrage index is a more comprehensive measure compared to liquidity and in fact, liquidity is just one of the six components that we have considered that contribute to limits of arbitrage.

As we move down Table 2.5 to higher limits of arbitrage groups namely the 0.41-0.60, 0.61-0.80 and the highest limits of arbitrage group 0.81-1.00, we notice a consistent trend that time taken to achieve both weak form and semi-strong form efficiency rises. Also, within a group the longer the time interval the lower the return predictability as demonstrated by the regression coefficients and their t-statistics.

To summarize, the results of the time taken to achieve market efficiency for the 0.41-0.60, 0.61-0.80 and 0.81-1.00 groups are as follows: weak form efficiency is achieved in three to five minutes for both 0.41-0.60 and 0.61-0.80 groups. However, the coefficients are more negative and significant for the 0.61-0.80 group at 5 minutes with a value of -0.031 and -0.030 for regressions based on Equation 2.4 and Equation 2.5 with corresponding t-statistics adjusted for cross correlation in residuals at -1.67 and -1.65 respectively. Whereas, for the group with a LOA (limits of arbitrage level) of 0.41-0.60 also achieves weak form efficiency in 3-5 minutes, however, its coefficients and their statistical significance is lower at 5 minutes. This further sheds light on the fact that limits of arbitrage which are imposed by regulations such as daily price limits and restrictions on short selling have a negative impact on market efficiency. These results are in line with past studies such as Chang, Luo, and Ren (2014) who find that a decrease in restrictions on short selling increases price efficiency in Chinese stock markets. Our study complements such findings by providing the first intraday evidence of their impact on Chinese stock markets.

2.3.3 Variance Ratio Tests and Time of the Day Effect

We find that bid-ask spreads vary across the day on any trading day. The bid ask spreads are plotted over every 5 minute interval from 9:30 am to 11:30 am and from 1:00 pm to 3:00 pm for all stocks aggregated over the entire sample period in Figure 2.1 (page 81). We see a pattern of high bid-ask spreads for the first few 5 minute intervals and then a monotonous decrease until the lunch break. This finding is consistent with the results of [Upson and Van Ness \(2017\)](#) who find that markets experience higher bid-ask spreads during the first few minutes and then a monotonous decline occurs.

After the lunch break there is a slight bump which is followed by a steady decline once again. Since liquidity plays a big role in market efficiency and facilitates market efficiency by enabling smooth arbitrage activity [Chordia, Roll, and Subrahmanyam \(2008\)](#), this variation in liquidity as measured in terms of transaction costs and the decrease in level of liquidity as the magnitude of the bid-ask spread rises provides us with an opportunity to study its impact. To further examine the impact of the time of the day in determining market liquidity and hence efficiency, we split the trading day in to 8 half-hour intervals and conduct variance ratio tests to determine the adherence to random walk. The interpretation of our results is based on the line of reasoning adapted by studies such as [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) who interpret the dominance of random walk if the variance ratio of a scaled long term horizon is the same as the variance ratio of a relatively shorter term horizon. We use two different variance ratios to ensure robustness in our interpretation.

The two different variance ratios that we consider are the ratios of the 1 minute and 30 minute intervals as utilized by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) and the variance ratios of 15 second to 5 minute intervals as utilized by [Conrad, Wahal, and Xiang \(2015\)](#). This helps us ensure that our results are robust to alternate specification of the short term and long term intervals of interest over which the variance ratios are examined to be linear and the ratio's convergence to unity is interpreted as a random walk.

In Table 2.6 we report the variance ratio tests over each half hour trading interval of the day for each sub group of stocks using scaled variances of 30 minute returns to 1 minute returns, based on the average daily LOA (Limits of Arbitrage) Index level. The time series averages of the cross sectional averages of these ratios are reported for each stock in each LOA index sub group. We observe that in the lowest LOA index group, the variance ratios are closer to 1 than any other group. The maximum value of the deviation of the ratio from unity on average is observed within the high limits of arbitrage group

with an LOA index level of 0.81-1.00. This further shows that limits of arbitrage have a great impact on intraday market efficiency. Also, we see that for high limits of arbitrage groups, the ratio is not only farther from unity, but it is also below unity. This suggests that variance ratios for the short intervals are higher than those of the long term intervals in the high limits of arbitrage group, since the short term intervals are the denominators and are multiplied by the number of short term intervals in one long term interval. This evidence is consistent with the findings of the study [Gu, Kang, and Xu \(2018\)](#) who find that higher limits of arbitrage explain higher idiosyncratic volatility.

In addition to these findings, Table 2.6 sheds light on a new pattern, previously undocumented by any other study to the best of our knowledge. Within each LOA index sub group we further divide each trading day in to 8 half hour intervals to account for the entire 4 hour trading day. We notice that the variance ratio is farthest apart from unity in the first half hour interval of the day which is 9:30 to 10:00 am. The variance ratio then begins to converge towards unity and deviates again at the closing interval before lunch i.e. the 11:00 to 11:30 am interval. Post lunch the cycle observed pre lunch is repeated with the a smaller spike observed again during the closing interval. Our findings are important for investors who would like to trade during more efficient times of the day and specially if they hold stocks that have higher limits of arbitrage. Also, this is an avenue of interest for regulators and policy makers who might take necessary steps to mitigate this discrepancy and time of the day effect in market efficiency.

We now turn our focus to Table 2.7 in which we report the variance ratio tests over each half hour trading interval of the day for each sub group of stocks using scaled variances of 5 minute returns to 15 second returns. This variation in the lengths of the intervals used to calculate variance ratios is quite important and is used in [Conrad, Wahal, and Xiang \(2015\)](#). This allows us to capture any significant differences that may arise in market efficiency due to factors such as high frequency or algorithmic trading. Our results are quite consistent with the previous variance ratio test where we used scaled variances of 30 minute intervals to 1 minute intervals. We see that higher limits of arbitrage groups experience a larger deviation from unity in the variance ratios. Furthermore, within each group we see the same intraday pattern where market efficiency is least during the first half hour of the day and then gradually improves during the remainder of the day only to decline somewhat towards the closing half hour of the day. This provides a robustness check for our first variance ratio measure and ensures that our findings are not driven by a particular combination of short and long term intervals and is robust to any alternative

specification as well.

The findings of the time of the day effect in market efficiency can be explained in the light of the fact that both volume and volatility are highest during the first half hour. This is due to the fact that market is absorbing any earnings announcements, over night information from domestic or overseas markets and important economic news releases and it takes about 30 minutes for the market to absorb this and eventually return to calm([Gao, Han, Li, and Zhou \(2018\)](#)).

2.3.4 The Impact of Shenzhen Connect on Market Efficiency

We now turn our focus on a landmark event in the Chinese markets which came with the introduction of Shenzhen connect on Shenzhen stock exchange's sub set of 881 stocks. Under this mechanisms foreign investors (both individual and institutional) registered on the Hong Kong stock exchange were allowed to invest in to Shenzhen stocks and this provision was over and above the quota restrictions imposed by Qualified Foreign Institutional Investors (QFII) and Renminbi Qualified Foreign Institutional Investor (hereafter RQFII). This program lead to increase in trading volume and has witnessed a steady flow of investment flowing in to Shenzhen stocks and increased trading volume as shown in [Figure 2.2](#)(page 82). This creates an opportunity to design a natural experiment to study the impact of reduction of limits of arbitrage (by virtue of increase in volume) on market efficiency.

We use the event study methodology employed by [Chang, Luo, and Ren \(2014\)](#) as explained in detail in the methodology section. Our event window is (-210 days,-31 days) as the pre-event window and (+31 days,+210 days) as the post event window. The Shenzhen connect started operating on December 5, 2016 so our pre-event and post event windows are 4th April, 2016 to 4th November, 2016 and the post event window is January 7th, 2017 to 7th August, 2017. We evaluate market efficiency using both our measures of efficiency- the intraday return predictability measure and the variance ratios.

The results for the impact of Shenzhen connect on market efficiency using the intraday return predictability measure are reported in [Table 2.8](#). We utilize [Equation 2.4](#) and [Equation 2.5](#) to determine the intraday return predictability measure. We see a decline across the coefficients of lagged returns and likewise in both order imbalance measures (*OINUM* and *OIVAL*). The sample of stocks in the pre-event window became efficient in greater than 5 minutes but in less than 10 minutes. However, in the post event window the coefficients on lagged order imbalances become insignificant in 5 minutes. Therefore,

the time taken to become semi-strong form efficient reduces and provides further evidence that limits of arbitrage such as price limit rule, short selling constraints and lack of availability of index futures can significantly impact market efficiency and increase the time taken to achieve market efficiency.

We now turn to the variance ratio measures to study the impact of reduction in limits of arbitrage from the advent of Shenzhen connect on the market efficiency of 881 stocks included in the program. The variance ratio test results are presented in Table 2.8. We employ both variance ratio measures i.e. the measure that uses the ratio of 30 minute return scaled variances to 1 minute variances and the one that uses the ratio of 5 minute return scaled variances to 15 second return variances. It is observed that for all 8 half hour return intervals from 9:30 to 11:30 am and from 1:00 to 3:00 pm there is a convergence of variance ratios towards unity. The deviation from unity is narrowed following the commencement of Shenzhen connect. The results are consistent across both measures of variance ratios. Therefore, it can be inferred that lowering of limits of arbitrage and easing regulations regarding participation of foreign investors in Chinese stocks has improved market efficiency.

2.3.5 The Impact of MSCI Inclusion on Market Efficiency

The next significant event that we intend to study is the historic event of the inclusion of mainland China A-shares inclusion in Morgan Stanley Capital International's Emerging markets index. This was widely expected to bring flows worth billions of dollars ¹¹ in to China's stocks. We study the impact of this event using the event study methodology employed by Chang, Luo, and Ren (2014) to study the impact of introduction of Margin Trading and Short Selling(MTSS) program on Chinese stocks using daily stock level data. This event will likely impact more than one factor affecting limits of arbitrage as well. It will lead to an increase in trading volume as more global funds flock to Chinese stocks. Also, it will lead to more analyst coverage as the demand and economic benefits associated with covering indexed stocks is higher than covering non index stocks.

Our event window is (-210 days,-31 days) as the pre-event window and (+31 days,+210 days) as the post event window. The 232 A-shares were added to the MSCI index on June 1, 2018. Our pre-event and post event windows are October 1, 2017 to May 1, 2018 and the post event window is July 2, 2018 to February 1, 2019. We evaluate market efficiency using both our measures of efficiency- the intraday return predictability measure and the

¹¹See <https://edition.cnn.com/2019/03/01/business/msci-china-stocks/index.html>

variance ratios.

The results for the intraday return predictability measure using Equation 2.4 and Equation 2.5 are presented in Table 2.9. The economic and statistical significance of all the regression coefficients on all three independent variables- lagged returns, lagged order imbalances in terms of the number of trades (*OINUM*) and the lagged order imbalances in terms of value of order imbalances (*OIVAL*) experience a decline in economic and statistical significance when examined in the pre-event and post event windows indicating that MSCI index inclusion improves market efficiency for the 232 A-shares included in the index. Also, the R^2 a higher value for which indicates a higher level of inefficiency, experiences a decline in the post event window relative to the pre event window for all time intervals of interest ranging from one minute to ten minutes.

The variance ratio tests are presented in Table 2.11 and point to greater adherence of a random walk in prices after inclusion in the index. We observe that across all 8 half hour trading intervals of the day the ratio shows greater convergence to unity and also demonstrates a smaller standard deviation in the estimates obtained. Overall, the twin evidence from the weakening of the intraday return predictability measure and convergence of variance ratios to unity in the post event window provides strong evidence of the positive impact of index inclusion in reducing price inefficiency and promoting market efficiency.

2.4 Conclusion

China's stock markets have often been compared to a casino which are irrational and have no link to fundamentals . We use the most recent data to examine intraday market efficiency in China across all stocks using two widely used measures of market efficiency- intraday return predictability measure(see Chordia, Roll, and Subrahmanyam (2005), Chordia, Roll, and Subrahmanyam (2008), Rösch, Subrahmanyam, and Van Dijk (2016)) and variance ratio tests (see Rösch, Subrahmanyam, and Van Dijk (2016), Conrad, Wahal, and Xiang (2015)). We use a unique Limits of Arbitrage index to group our stocks and then conduct the analyses on these groups. Our analyses indicates that higher limits of arbitrage measured by unique features of the Chinese stock markets such as the price limit rule, short selling restrictions and unavailability of futures contracts on non-index stocks inhibit market efficiency and are the reason behind its inefficiency.

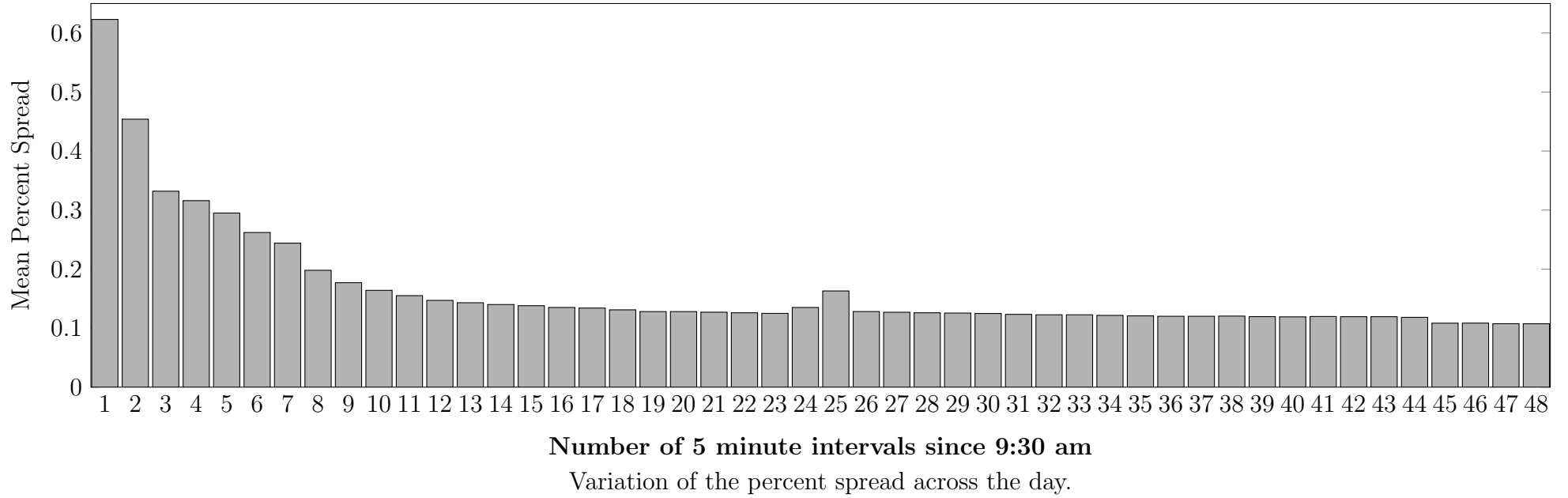
Stocks that have the lowest limits of arbitrage converge to market efficiency in the shortest amount of time as depicted by the regression coefficients and their economic

significance for the intraday return predictability measure and least divergence from unity for both specifications of the variance ratios calculated. Consistent with studies such as [Chordia, Roll, and Subrahmanyam \(2005\)](#) and [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) we find that markets converge to weak form market efficiency (as measured by the time taken for the lagged return co-efficient to become insignificant for regressions in Equation 2.4 and Equation 2.5 across all LOA index groups is lower than the time required the market to show semi strong form efficiency (as measured by the time taken by lagged order imbalance coefficients to show insignificance).

Most importantly, we document a time of the day effect in market efficiency with the first half hour showing the least amount of market efficiency in terms of the highest deviation of variance ratios from unity across all LOA groups. This can be attributed to the highest bid-ask spreads in the first half hour of the day as shown in Figure 2.1 (page 81). This information can be used by investors to trade in intervals of choice depending on their goals. For example, arbitrageurs may find the least efficient times to be more useful as their purpose is to engage in counter transactions and remove price discrepancy. On the other hand, ordinary risk averse investors may wait for the first half hour to pass and trade when the markets are more settled so as to avoid facing undesirable volatility.

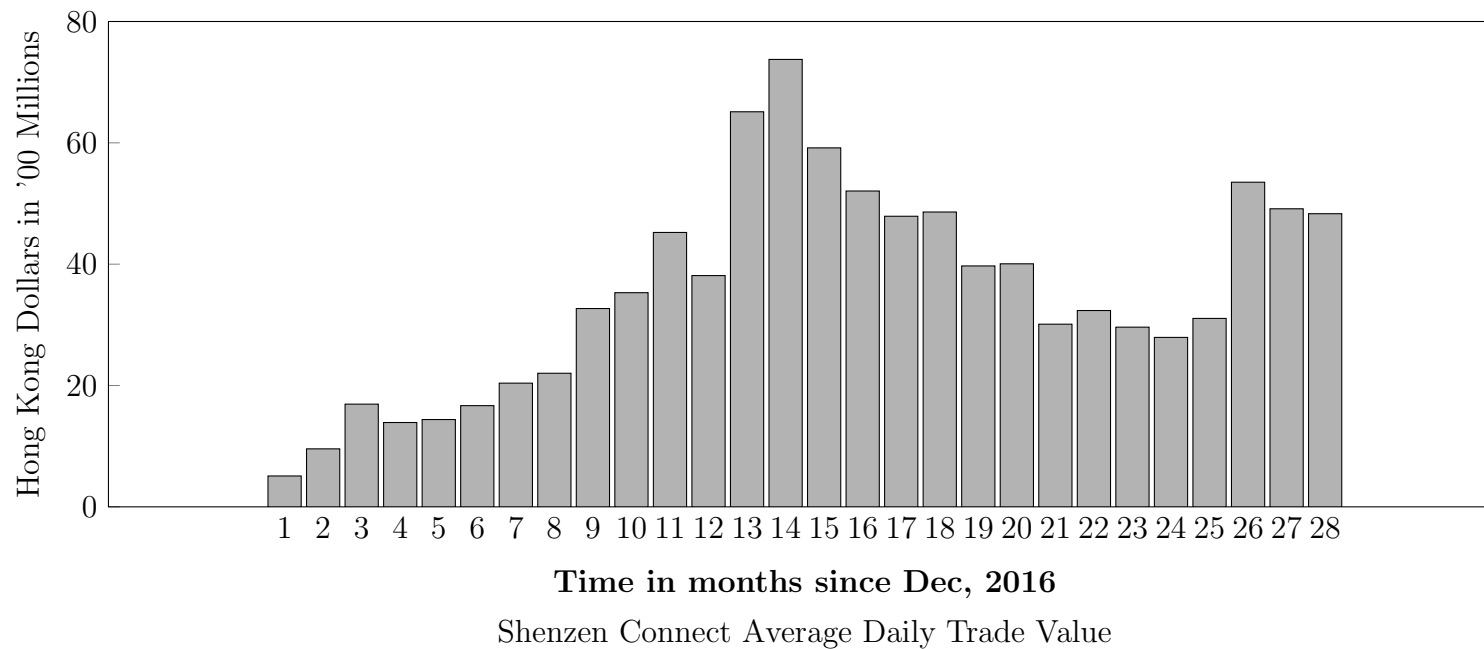
Our study also sheds light on the fact that the efforts of Chinese policy makers to reduce trading restrictions and improvement of various shortcomings in market structure which have paved the way for inclusion of Chinese A-shares in to the global MSCI emerging markets index have proved to be a bane for stocks. Using the event study methodology adapted by [Chang, Luo, and Ren \(2014\)](#), we have successfully shown that these two landmark events have improved market efficiency for affected stocks using both the intraday return predictability measure and variance ratio measures showing improvement in market efficiency in the post event window. Overall, it further supports the notion that lower limits of arbitrage facilitate market efficiency.

Figure 2.1: Mean Percent Spread for each 5 Minute Interval of the Trading Day



This figure depicts intraday market liquidity. The mean percent spread is plotted for every 5 minute spread which is the average of the percent spread of all 3473 A-shares listed on both Shanghai and Shenzhen exchanges. The time period for which this is done is 1st April, 2016 to 1st April, 2019.

Figure 2.2: Average Daily Value of Trades through the Shenzhen Connect



This figure shows the average daily traded value of stocks bought and sold by foreign investors registered on the Hong Kong Stock Exchange using the Shenzhen stock connect since the program started in December, 2016. The amounts have been obtained from the Hong Stock Exchange's website and are reported in multiples of 100 million Hong Kong Dollars.

Table 2.1 : Overview of the Chinese Stock Market

Our sample period extends from 1st April, 2016 to 1st March, 2019. We consider all Chinese A-shares in our analyses which includes 1344 stocks listed at the Shanghai Stock Exchange. Also, we consider all A-shares listed at the Shenzhen Stock Exchange including 463 stocks listed on the Main Board, 921 stocks listed on the SME Board and 745 stocks listed on the SME Board. The Mean Market Capitalisation and Average P/E ratios for all the components are also listed.

Exchange	Number of Stocks	Mean Market Capitalisation (Billions)
Shanghai(A-shares)	1344	18.75
Shenzen(All Boards- A-shares)	2129	10.15
Shenzen(Main Board- A-shares)	463	15.72
Shenzen(SME Board A-shares)	921	9.87
Shenzen(ChiNext Board A-shares)	745	7.05
Total(All A-shares)	3473	13.47

Table 2.2 : Distribution of Limits of Arbitrage Index

The table reports the distribution of limits-of-arbitrage index. The table reports the average over the entire sample period of the cross sectional distribution of the Limits of Arbitrage index in line with [Gu, Kang, and Xu \(2018\)](#). In the first step, we estimate the cross-sectional distribution of limits-of-arbitrage index for each day. Then we calculate the time-series average of distributions obtained in the first step. The limits-of-arbitrage index is the average of six limits-of-arbitrage indicators, consisting of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage.

Limits of Arbitrage	Number	Percentage
0-0.20	740	21.31
0.21-0.40	632	18.19
0.41-0.60	602	17.33
0.61-0.80	886	25.52
0.81-1.00	613	17.65
Total	3473	100

Table 2.3 : Summary Statistics of Key Variables

This table reports the cross-sectional mean, standard deviation, minimum and maximum of the time series average by stock for the Midpoint Returns, OINUM and OIVAL over a one minute interval. The data to compute all the variables is collected from Bloomberg. For better presentation, the mean Midpoint Returns are multiplied by 10^6 .

Variable	Stocks	Mean	SD	Minimum	Maximum
1-minute interval					
<i>MidpointReturns</i>	3473	-1.06	0.001	-0.087	0.059
<i>OINUM</i>	3473	0.0194	0.151	-0.756	0.658
<i>OIVAL</i>	3473	2332	15468	-56200	125000
2-minute interval					
<i>MidpointReturns</i>	3473	-1.19	0.001	-0.10	0.10
<i>OINUM</i>	3473	0.0214	0.163	-0.823	0.742
<i>OIVAL</i>	3473	4159	30125	-12010	250000

Table 2.4 : Multivariate Regressions Based on Entire Sample

Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzhen stock markets. The return is computed from the midpoint of the quotes prevailing at the beginning and end of each short term time interval (from one to ten minutes); *OINUM* is the number of buyer-initiated less the number of seller-initiated trades during the same time interval as the return; and *OIVAL* is the total domestic currency amount expended by buyer-initiators less the total domestic currency amount received by seller-initiators during that interval divided by the total trade value. The first interval of each day is excluded and all other interval observations are included in the same regression. As implemented by [Chordia, Roll, and Subrahmanyam \(2005\)](#) a separate regression is estimated for each individual stock. The cross-sectional mean of the estimated regression coefficient is presented in the first row. The average t-statistic from the individual stock regressions is reported in the second row and is enclosed in parentheses. Finally the t-statistic computed by adjusting for cross-correlation in the residuals and is reported in the third row. The R^2 is the adjusted R-square in percent and is computed as the cross sectional average of individual adjusted R-square. For better presentation and inclusion, the coefficients for *OINUM* and *OIVAL* are multiplied by 10^6 and 10^9 respectively. In the fourth row for each variable the standardized coefficient is reported.

Variable	Return Interval (Minutes)									
	One		Two		Three		Five		Ten	
Mid Point	-0.050	-0.049	- 0.038	- 0.037	-0.033	-0.032	- 0.027	-0.026	-0.016	-0.014
$Return_{t-1}$	(-5.85)	(-5.80)	(-4.63)	(-4.57)	(-3.71)	(-3.67)	(-2.02)	(-1.99)	(-0.80)	(-0.79)
	(-3.72)	(-3.68)	(-2.79)	(-2.75)	(-2.06)	(-2.07)	(-1.10)	(-1.07)	(-0.37)	(-0.35)
	-0.05	-0.05	- 0.04	- 0.04	-0.03	-0.03	- 0.03	-0.03	-0.02	-0.01
$OINUM_{t-1}$	0.99		0.88		0.83		0.75		0.32	
	(6.73)		(5.75)		(4.80)		(3.93)		(2.22)	
	(4.62)		(3.87)		(3.05)		(2.82)		(1.39)	
	0.44		0.40		0.36		0.25		0.12	
$OIVAL_{t-1}$		2.45		2.15		1.48		0.98		0.67
		(6.41)		(5.59)		(4.99)		(3.97)		(2.35)
		(4.37)		(3.63)		(2.95)		(2.67)		(1.69)
		0.41		0.37		0.30		0.22		0.10
R^2	1.20	1.18	1.08	1.07	0.81	0.79	0.53	0.52	0.23	0.22

Table 2.5 : Multivariate Regressions Based on Limits of Arbitrage Index

Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzhen stock markets. The return is computed from the midpoint of the quotes prevailing at the beginning and end of each short term time interval (from one to ten minutes); *OINUM* is the number of buyer-initiated less the number of seller-initiated trades during the same time interval as the return; and *OIVAL* is the total domestic currency amount expended by buyer-initiators less the total domestic currency amount received by seller-initiators during that interval divided by the total trade value. The stocks are grouped in five different categories of the LOA index with the group 0.00 to 0.20 having the lowest limits of arbitrage. The first interval of each day is excluded and all other interval observations are included in the same regression. As implemented by Chordia, Roll, and Subrahmanyam (2005) a separate regression is estimated for each individual stock. The cross-sectional mean of the estimated regression coefficient is presented in the first row. The average t-statistic from the individual stock regressions is reported in the second row and is enclosed in parentheses. Finally the t-statistic computed by adjusting for cross-correlation in the residuals and is reported in the third row. The R^2 is the adjusted R-square in percent and is computed as the cross sectional average of individual adjusted R-square. For better presentation and inclusion, the coefficients for *OINUM* and *OIVAL* are multiplied by 10^6 and 10^9 respectively. In the fourth row for each variable the standardized coefficient is reported.

Variable	Return Interval (Minutes)									
	One		Two		Three		Five		Ten	
Limits of Arbitrage Index between 0.00 and 0.20(740 Stocks)										
Mid Point	-0.037	-0.034	- 0.029	- 0.028	-0.025	-0.023	- 0.020	-0.018	-0.012	-0.011
$Return_{t-1}$	(-3.05)	(-3.02)	(-2.42)	(-2.40)	(-2.22)	(-2.15)	(-1.06)	(-1.01)	(-0.24)	(-0.23)
	(-1.84)	(-1.82)	(-1.52)	(-1.45)	(-1.33)	(-1.25)	(-0.65)	(-0.63)	(-0.15)	(-0.14)
	-0.04	-0.03	- 0.03	- 0.03	-0.03	-0.02	- 0.02	-0.02	-0.01	-0.01
$OINUM_{t-1}$	0.88		0.84		0.78		0.67		0.26	
	(4.45)		(3.11)		(2.73)		(2.31)		(1.85)	
	(3.09)		(1.84)		(1.53)		(1.32)		(1.09)	
	0.30		0.25		0.19		0.12		0.04	
$OIVAL_{t-1}$		2.21		1.84		1.21		0.76		0.54
		(4.56)		(3.22)		(2.68)		(2.33)		(1.78)
		(3.11)		(1.89)		(1.45)		(1.28)		(1.02)
		0.26		0.21		0.15		0.08		0.02
R^2	1.02	1.01	0.94	0.92	0.70	0.67	0.45	0.42	0.17	0.16
Limits of Arbitrage Index between 0.21 and 0.40(632 Stocks)										
Mid Point	-0.042	-0.041	- 0.032	- 0.030	-0.027	-0.026	- 0.022	-0.021	-0.013	-0.011
$Return_{t-1}$	(-5.33)	(-5.25)	(-3.45)	(-3.37)	(-2.36)	(-2.34)	(-1.07)	(-1.05)	(-0.25)	(-0.24)
	(-3.29)	(-3.27)	(-2.26)	(-2.19)	(-1.88)	(-1.77)	(-0.67)	(-0.65)	(-0.15)	(-0.14)
	-0.04	-0.04	- 0.03	- 0.03	-0.03	-0.03	- 0.02	-0.02	-0.01	-0.01
$OINUM_{t-1}$	0.95		0.86		0.79		0.70		0.28	
	(5.29)		(4.76)		(3.24)		(3.22)		(1.90)	
	(4.04)		(3.36)		(2.25)		(1.97)		(1.12)	
	0.33		0.28		0.22		0.14		0.07	
$OIVAL_{t-1}$		2.37		1.97		1.32		0.82		0.60
		(5.19)		(4.48)		(3.85)		(2.58)		(1.92)
		(4.06)		(3.25)		(2.49)		(1.61)		(1.03)
		0.29		0.24		0.18		0.12		0.05
R^2	1.15	1.12	1.02	1.00	0.72	0.69	0.47	0.45	0.17	0.16

(Continued)

Table 2.5 – Continued

Variable	Return Interval (Minutes)									
	One		Two		Three		Five		Ten	
Limits of Arbitrage Index between 0.41 and 0.60(602 stocks)										
Mid Point	-0.046	-0.047	- 0.035	- 0.036	-0.030	-0.032	- 0.028	-0.026	-0.014	-0.012
$Return_{t-1}$	(-5.53)	(-5.55)	(-3.67)	(-3.65)	(-2.55)	(-2.48)	(-1.25)	(-1.17)	(-0.29)	(-0.28)
	(-3.58)	(-3.49)	(-2.75)	(-2.59)	(-2.16)	(-1.98)	(-0.85)	(-0.77)	(-0.18)	(-0.17)
	-0.05	-0.05	- 0.04	- 0.04	-0.03	-0.03	- 0.03	-0.03	-0.01	-0.01
$OINUM_{t-1}$	0.97		0.90		0.82		0.75		0.30	
	(5.43)		(4.89)		(4.41)		(3.52)		(1.96)	
	(4.16)		(3.47)		(2.85)		(2.56)		(1.18)	
	0.35		0.31		0.25		0.16		0.10	
$OIVAL_{t-1}$		2.45		2.15		1.49		0.98		0.66
		(5.26)		(4.64)		(4.35)		(3.48)		(2.52)
		(4.17)		(3.43)		(2.67)		(2.42)		(1.65)
		0.31		0.26		0.21		0.15		0.08
R^2	1.17	1.15	1.04	1.03	0.76	0.74	0.51	0.49	0.21	0.20
Limits of Arbitrage Index between 0.61 and 0.80(886 Stocks)										
Mid Point	-0.058	-0.057	- 0.041	- 0.040	-0.036	-0.035	- 0.031	-0.030	-0.018	-0.017
$Return_{t-1}$	(-7.33)	(-7.25)	(-6.45)	(-6.37)	(-5.36)	(-5.34)	(-3.07)	(-3.05)	(-1.25)	(-1.24)
	(-4.29)	(-4.27)	(-3.26)	(-3.19)	(-2.79)	(-2.74)	(-1.67)	(-1.65)	(-0.75)	(-0.73)
	-0.06	-0.06	- 0.04	- 0.04	-0.04	-0.04	- 0.03	-0.03	-0.02	-0.02
$OINUM_{t-1}$	1.02		0.92		0.85		0.79		0.35	
	(8.89)		(7.76)		(6.24)		(5.22)		(2.50)	
	(6.14)		(4.36)		(3.35)		(3.07)		(1.62)	
	0.37		0.33		0.29		0.20		0.13	
$OIVAL_{t-1}$		2.58		2.33		1.62		1.05		0.78
		(8.20)		(7.45)		(6.76)		(5.37)		(2.68)
		(6.05)		(4.28)		(3.42)		(3.16)		(1.74)
		0.34		0.29		0.24		0.19		0.12
R^2	1.25	1.20	1.12	1.09	0.85	0.83	0.55	0.54	0.30	0.28
Limits of Arbitrage Index between 0.81 and 1.00(613 Stocks)										
Mid Point	-0.068	-0.066	- 0.054	- 0.052	-0.048	-0.045	- 0.035	-0.033	-0.022	-0.019
$Return_{t-1}$	(-8.02)	(-7.84)	(-6.87)	(-6.75)	(-5.77)	(-5.52)	(-3.51)	(-3.42)	(-1.95)	(-1.87)
	(-5.35)	(-4.52)	(-3.65)	(-3.48)	(-3.23)	(-3.20)	(-2.35)	(-2.33)	(-0.98)	(-0.94)
	-0.07	-0.07	- 0.06	- 0.05	-0.05	-0.05	- 0.04	-0.03	-0.02	-0.02
$OINUM_{t-1}$	1.15		0.94		0.88		0.82		0.38	
	(9.25)		(8.22)		(6.62)		(5.86)		(2.86)	
	(6.42)		(4.66)		(3.59)		(3.22)		(1.97)	
	0.44		0.37		0.32		0.25		0.16	
$OIVAL_{t-1}$		2.66		2.45		1.73		1.14		0.86
		(8.45)		(7.84)		(7.05)		(5.84)		(2.83)
		(6.24)		(4.69)		(3.68)		(3.27)		(1.79)
		0.37		0.33		0.28		0.23		0.16
R^2	1.32	1.28	1.20	1.18	0.94	0.90	0.66	0.64	0.35	0.31

Table 2.6 : Variance Ratios based on Scaled 30 Minute to 1 Minute Return Variances

The sample consists of all stocks listed on Shanghai and Shenzhen stock exchanges. The combined number of A-shares listed on all exchanges and boards in China is 3473 for the entire period of our study extending from 1st April, 2016 to 1st April, 2019. For each half hour interval (for each firm), we calculate variance ratios based on 1 minute and 30 minute mid-quote returns. The first row in the table reports time series averages of the cross sectional averages of these variance ratios. The time series average of the cross sectional standard deviation is in parentheses. The intervals are numbered from 1 to 4, for each half hour interval between 9:30 am and 11:30 am for the pre lunch session, and for the post lunch session the intervals are numbered from 5 to 8 for the time interval between 1:00 pm to 3:00 pm. The first interval 1 represents the time period from 9:30-10:00 am, interval 2 represents the time period from 10:00-10:30 am, interval 3 represents the time interval from 10:30- 11:00 am and so on until interval 8 represents 2:30-3:00 pm. LOA represents the Limits of Arbitrage Index calculated as per the [Gu, Kang, and Xu \(2018\)](#).

LOA	Time intervals							
	1	2	3	4	5	6	7	8
0.00-0.20	1.05 (0.46)	1.03 (0.44)	1.02 (0.43)	1.03 (0.45)	1.03 (0.43)	1.02 (0.42)	1.01 (0.40)	1.02 (0.41)
0.21-0.40	1.06 (0.50)	1.04 (0.47)	1.03 (0.45)	1.03 (0.46)	1.04 (0.44)	1.03 (0.43)	1.02 (0.41)	1.03 (0.42)
0.41-0.60	0.93 (0.51)	0.94 (0.49)	0.95 (0.46)	0.94 (0.47)	0.94 (0.47)	0.95 (0.46)	0.94 (0.45)	0.93 (0.48)
0.61-0.80	0.90 (0.55)	0.92 (0.53)	0.91 (0.50)	0.92 (0.54)	0.91 (0.54)	0.92 (0.53)	0.93 (0.52)	0.92 (0.54)
0.81-1.00	0.85 (0.58)	0.88 (0.57)	0.90 (0.55)	0.87 (0.56)	0.87 (0.55)	0.90 (0.54)	0.92 (0.55)	0.90 (0.56)

Table 2.7 : Variance Ratios Based on Scaled 5 Minute to 15 Second Returns

The sample consists of all stocks listed on Shanghai and Shenzhen stock exchanges. The combined number of A-shares listed on all exchanges and boards in China is 3473 for the entire period of our study extending from 1st April, 2016 to 1st April, 2019. For each half hour interval (for each firm), we calculate variance ratios based on 15 second and 5 minute mid-quote returns. The first row in the table reports time series averages of the cross sectional averages of these variance ratios. The time series average of the cross sectional standard deviation is in parentheses. The intervals are numbered from 1 to 4, for each half hour interval between 9:30 am and 11:30 am for the pre lunch session, and for the post lunch session the intervals are numbered from 5 to 8 for the time interval between 1:00 pm to 3:00 pm. The first interval 1 represents the time period from 9:30-10:00 am, interval 2 represents the time period from 10:00-10:30 am, interval 3 represents the time interval from 10:30- 11:00 am and so on until interval 8 represents 2:30-3:00 pm. LOA is the Limits of Arbitrage Index created as per [Gu, Kang, and Xu \(2018\)](#).

LOA	Time intervals							
	1	2	3	4	5	6	7	8
0.00-0.20	1.07 (0.50)	1.05 (0.47)	1.03 (0.46)	1.04 (0.48)	1.04 (0.46)	1.03 (0.45)	1.02 (0.43)	1.04 (0.44)
0.21-0.40	1.09 (0.52)	1.07 (0.49)	1.06 (0.45)	1.07 (0.47)	1.06 (0.47)	1.05 (0.45)	1.04 (0.44)	1.05 (0.43)
0.41-0.60	0.90 (0.55)	0.92 (0.54)	0.93 (0.50)	0.92 (0.51)	0.93 (0.50)	0.94 (0.49)	0.92 (0.48)	0.93 (0.50)
0.61-0.80	0.88 (0.58)	0.90 (0.57)	0.89 (0.54)	0.90 (0.56)	0.90 (0.56)	0.91 (0.55)	0.90 (0.54)	0.90 (0.53)
0.81-1.00	0.83 (0.60)	0.86 (0.58)	0.88 (0.57)	0.87 (0.60)	0.87 (0.60)	0.88 (0.59)	0.87 (0.58)	0.88 (0.59)

Table 2.8 : Multivariate Regressions for the Impact of Shenzen Connect

Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzen stock markets. Only the 881 stocks that were initially included on Shenzen connect on December 5th, 2016 are included in the regression. We report our results for a pre-event window which ranges from 1st April, 2016 to 4th November, 2016. This ensures that we drop the 31 days immediately preceding the event as recommended by [Chang, Cheng, and Yu \(2007\)](#) and also adopted by [Chang, Luo, and Ren \(2014\)](#). Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzen stock markets. The return is computed from the midpoint of the quotes prevailing at the beginning and end of each short term time interval (from one to ten minutes); *OINUM* is the number of buyer-initiated less the number of seller-initiated trades during the same time interval as the return; and *OIVAL* is the total domestic currency amount expended by buyer-initiators less the total domestic currency amount received by seller-initiators during that interval divided by the total trade value. The first interval of each day is excluded and all other interval observations are included in the same regression. As implemented by [Chordia, Roll, and Subrahmanyam \(2005\)](#) a separate regression is estimated for each individual stock. The cross-sectional mean of the estimated regression coefficient is presented in the first row. The average t-statistic from the individual stock regressions is reported in the second row and is enclosed in parentheses. Finally the t-statistic computed by adjusting for cross-correlation in the residuals and is reported in the third row. The R^2 is the adjusted R-square in percent and is computed as the cross sectional average of individual adjusted R-square. For better presentation and inclusion, the coefficients for *OINUM* and *OIVAL* are multiplied by 10^6 and 10^9 respectively. In the fourth row for each variable the standardized coefficient is reported.

Variable	Return Interval (Minutes)									
	One		Two		Three		Five		Ten	
Pre-Event Window										
Mid Point	-0.043	-0.042	- 0.034	- 0.033	-0.028	-0.026	- 0.025	-0.023	-0.014	-0.013
$Return_{t-1}$	(-4.86)	(-4.78)	(-3.53)	(-3.57)	(-2.47)	(-2.43)	(-1.25)	(-1.22)	(-0.27)	(-0.25)
	(-3.45)	(-3.41)	(-2.59)	(-2.55)	(-1.98)	(-1.86)	(-0.74)	(-0.73)	(-0.17)	(-0.16)
	-0.04	-0.04	- 0.03	- 0.03	-0.03	-0.03	- 0.03	-0.02	-0.01	-0.01
$OINUM_{t-1}$	0.96		0.88		0.80		0.73		0.29	
	(4.93)		(4.44)		(4.07)		(3.41)		(1.94)	
	(4.08)		(3.41)		(2.55)		(2.29)		(1.16)	
	0.34		0.30		0.27		0.16		0.10	
$OIVAL_{t-1}$		2.42		2.06		1.41		0.89		0.62
		(4.87)		(4.56)		(4.15)		(3.07)		(2.28)
		(4.13)		(3.35)		(2.59)		(2.05)		(1.44)
		0.31		0.26		0.21		0.15		0.08
R^2	1.16	1.14	1.04	1.02	0.75	0.72	0.50	0.47	0.20	0.19
Post-Event Window										
Mid Point	-0.042	-0.041	- 0.033	- 0.031	-0.026	-0.025	- 0.023	-0.021	-0.013	-0.012
$Return_{t-1}$	(-4.77)	(-4.70)	(-3.45)	(-3.40)	(-2.41)	(-2.39)	(-1.19)	(-1.18)	(-0.26)	(-0.25)
	(-3.39)	(-3.36)	(-2.51)	(-2.47)	(-1.94)	(-1.83)	(-0.72)	(-0.70)	(-0.16)	(-0.15)
	-0.04	-0.04	- 0.03	- 0.03	-0.03	-0.03	- 0.02	-0.02	-0.01	-0.01
$OINUM_{t-1}$	0.94		0.86		0.78		0.71		0.26	
	(4.85)		(4.36)		(3.89)		(3.27)		(1.85)	
	(3.98)		(3.35)		(2.47)		(1.99)		(1.04)	
	0.32		0.28		0.24		0.13		0.08	
$OIVAL_{t-1}$		2.36		1.95		1.32		0.81		0.57
		(4.75)		(4.44)		(4.03)		(2.95)		(2.08)
		(4.03)		(3.21)		(2.50)		(1.98)		(1.22)
		0.29		0.23		0.19		0.13		0.05
R^2	1.14	1.13	1.03	1.01	0.72	0.70	0.48	0.46	0.19	0.17

Table 2.9 : Multivariate Regressions for the Impact of MSCI Index Inclusion

Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzhen stock markets. The 232 A-shares were added to the MSCI index on June 1, 2018. Our pre-event and post event windows are October 1, 2017 to May 1, 2018 and the post event window is July 2, 2018 to February 1, 2019. This ensures that we drop the 31 days immediately preceding the event as recommended by [Chang, Cheng, and Yu \(2007\)](#) and also adopted by [Chang, Luo, and Ren \(2014\)](#). Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzhen stock markets. The return is computed from the midpoint of the quotes prevailing at the beginning and end of each short term time interval (from one to ten minutes); *OINUM* is the number of buyer-initiated less the number of seller-initiated trades during the same time interval as the return; and *OIVAL* is the total domestic currency amount expended by buyer-initiators less the total domestic currency amount received by seller-initiators during that interval divided by the total trade value. The first interval of each day is excluded and all other interval observations are included in the same regression. As implemented by [Chordia, Roll, and Subrahmanyam \(2005\)](#) a separate regression is estimated for each individual stock. The cross-sectional mean of the estimated regression coefficient is presented in the first row. The average t-statistic from the individual stock regressions is reported in the second row and is enclosed in parentheses. Finally the t-statistic computed by adjusting for cross-correlation in the residuals and is reported in the third row. The R^2 is the adjusted R-square in percent and is computed as the cross sectional average of individual adjusted R-square. For better presentation and inclusion, the coefficients for *OINUM* and *OIVAL* are multiplied by 10^6 and 10^9 respectively. In the fourth row for each variable the standardized coefficient is reported.

	Return Interval (Minutes)									
Variable	One		Two		Three		Five		Ten	
Pre-Event window										
Mid Point	-0.033	-0.031	- 0.027	- 0.025	-0.022	-0.021	- 0.018	-0.016	-0.011	-0.010
$Return_{t-1}$	(-2.20)	(-2.12)	(-1.42)	(-1.40)	(-1.23)	(-1.20)	(-0.86)	(-0.84)	(-0.20)	(-0.13)
	(-1.67)	(-1.62)	(-1.35)	(-1.31)	(-1.11)	(-1.02)	(-0.65)	(-0.60)	(-0.18)	(-0.17)
	-0.03	-0.03	- 0.03	- 0.03	-0.02	-0.02	- 0.02	-0.02	-0.01	-0.01
$OINUM_{t-1}$	0.85		0.82		0.74		0.63		0.20	
	(3.10)		(2.75)		(2.36)		(1.80)		(1.23)	
	(2.16)		(1.66)		(1.42)		(1.28)		(1.05)	
	0.27		0.22		0.16		0.10		0.03	
$OIVAL_{t-1}$		2.02		1.75		1.15		0.65		0.42
		(3.09)		(2.64)		(1.46)		(1.16)		(0.94)
		(2.18)		(1.63)		(1.40)		(1.11)		(0.91)
		0.24		0.19		0.13		0.06		0.02
R^2	0.95	0.94	0.92	0.91	0.68	0.65	0.42	0.40	0.15	0.14
Post-Event Window										
Mid Point	-0.031	-0.029	-0.025	- 0.023	- 0.019	-0.018	-0.016	- 0.015	-0.009	-0.008
$Return_{t-1}$	(-2.15)	(-2.10)	(-1.38)	(-1.35)	(-1.18)	(-1.15)	(-0.83)	(-0.80)	(-0.15)	(-0.10)
	(-1.60)	(-1.58)	(-1.32)	(-1.28)	(-1.07)	(-1.00)	(-0.76)	(-0.72)	(-0.14)	(-0.09)
	-0.03	-0.03	-0.03	- 0.02	- 0.02	-0.02	-0.02	- 0.02	-0.01	-0.01
$OINUM_{t-1}$	0.83		0.80		0.71		0.60		0.18	
	(3.05)		(2.71)		(2.30)		(1.73)		(1.18)	
	(2.09)		(1.61)		(1.35)		(1.22)		(1.01)	
	0.25		0.20		0.14		0.08		0.02	
$OIVAL_{t-1}$		1.95		1.71		1.11		0.61		0.37
		(3.05)		(2.55)		(1.40)		(1.12)		(0.91)
		(1.87)		(1.50)		(1.31)		(1.01)		(0.88)
		0.22		0.17		0.12		0.05		0.02
R^2	0.90	0.89	0.85	0.84	0.63	0.62	0.40	0.38	0.14	0.12

Table 2.10 : Variance Ratio Tests for the Impact of Shenzen Connect

The sample consists of stocks listed Shenzen stock exchange that are part of Shenzen connect. The combined number of A-shares listed on the Shenzen exchange today is 881 stocks for the pre-event window 1st April, 2016 to 4th November, 2016 and the post event window extending from 6th January, 2017 to 10th July, 2017. For each half hour interval (for each firm), we calculate variance ratios based on 15 second and 5 minute mid-quote returns. The first row in the table reports time series averages of the cross sectional averages of these variance ratios. The time series average of the cross sectional standard deviation is in parentheses. The intervals are numbered from 1 to 4, for each half hour interval between 9:30 am and 11:30 am for the pre lunch session, and for the post lunch session the intervals are numbered from 5 to 8 for the time interval between 1:00 pm to 3:00 pm. The first interval 1 represents the time period from 9:30-10:00 am, interval 2 represents the time period from 10:00-10:30 am, interval 3 represents the time interval from 10:30- 11:00 am and so on until interval 8 represents 2:30-3:00 pm.

Shenzen Connect	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event Window								
15 sec to 5 min	1.06 (0.45)	1.04 (0.42)	1.03 (0.43)	1.04 (0.44)	1.04 (0.44)	1.02 (0.43)	1.02 (0.42)	1.03 (0.44)
Post-Event Window								
15 sec to 5 min	1.05 (0.44)	1.03 (0.42)	1.02 (0.42)	1.03 (0.43)	1.03 (0.42)	1.02 (0.41)	1.02 (0.42)	1.03 (0.43)
Shenzen connect	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event Window								
1 min to 30 min	1.05 (0.44)	1.04 (0.43)	1.03 (0.42)	1.04 (0.43)	1.04 (0.43)	1.03 (0.42)	1.02 (0.41)	1.03 (0.43)
Post-Event Window								
1 min to 30 min	1.03 (0.41)	1.02 (0.40)	1.02 (0.40)	1.03 (0.41)	1.03 (0.41)	1.02 (0.40)	1.02 (0.39)	1.03 (0.40)

Table 2.11 : Variance Ratio Tests for the Impact of MSCI Inclusion

The sample consists of stocks listed Shenzhen stock exchange that are part of Shenzhen connect. The 232 A-shares were added to the MSCI index on June 1, 2018. Our pre-event and post event windows are October 1, 2017 to May 1, 2018 and the post event window is July 2, 2018 to February 1, 2019. For each half hour interval (for each firm), we calculate variance ratios based on 15 second and 5 minute mid-quote returns. The first row in the table reports time series averages of the cross sectional averages of these variance ratios. The time series average of the cross sectional standard deviation is in parentheses. The intervals are numbered from 1 to 4, for each half hour interval between 9:30 am and 11:30 am for the pre lunch session, and for the post lunch session the intervals are numbered from 5 to 8 for the time interval between 1:00 pm to 3:00 pm. The first interval 1 represents the time period from 9:30-10:00 am, interval 2 represents the time period from 10:00-10:30 am, interval 3 represents the time interval from 10:30- 11:00 am and so on until interval 8 represents 2:30-3:00 pm.

MSCI Inclusion	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event Window								
15 sec to 5 min	1.04 (0.43)	1.03 (0.40)	1.03 (0.42)	1.04 (0.43)	1.04 (0.43)	1.03 (0.42)	1.02 (0.41)	1.04 (0.42)
Post-Event Window								
15 sec to 5 min	1.03 (0.42)	1.02 (0.39)	1.02 (0.40)	1.02 (0.41)	1.03 (0.41)	1.02 (0.40)	1.02 (0.39)	1.03 (0.40)
MSCI inclusion	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event Window								
1 min to 30 min	1.03 (0.42)	1.02 (0.40)	1.02 (0.41)	1.03 (0.42)	1.03 (0.42)	1.02 (0.41)	1.02 (0.41)	1.03 (0.42)
Post-Event Window								
1 min to 30 min	1.02 (0.40)	1.01 (0.37)	1.00 (0.38)	1.01 (0.39)	1.01 (0.39)	1.00 (0.38)	1.01 (0.37)	1.01 (0.38)

Chapter 3

The Impact of Political, Economic and Trade Policy Uncertainty on Market Liquidity and Market Efficiency

“For us at the IMF, it’s imperative that trade tensions are resolved in a way satisfying for everyone because clearly tensions between the United States and China are the threat to the global economy.”¹

(Christine Lagarde, Head, International Monetary Fund.)

3.1 Introduction

In recent years there has been a spike in political uncertainty. Two major events that have caught the spotlight most recently are the unexpected Brexit vote of 2016 and the election of Donald Trump as the US President in 2016. Following these events there has been a surge in interest to study the impact of political uncertainty on various aspects of corporations and financial markets. Jens (2017) provides an insight in to the impact of political uncertainty on firm investment by considering periods before and after gubernatorial elections in the United States. Another study, Çolak, Durnev, and Qian (2017) looks at the impact of U.S. gubernatorial elections on IPO activity and find that there is lower IPO activity in states that are about to witness a gubernatorial election. Kelly, Pástor, and Veronesi (2016) study option markets and find that options that last through close presidential elections and global summits are priced higher indicating that the buyers are

¹See the New York Times article available at: <https://www.nytimes.com/reuters/2019/05/07/business/07reuters-usa-trade-china-imf.html>

willing to pay a premium on options hedging them against political uncertainty that may lead to higher volatility, tail risk and price crashes.

[Addoum and Kumar \(2016\)](#) find that a change in political sentiment and the political uncertainty arising from it affects the returns on politically sensitive firms and industries. [Marshall, Nguyen, Nguyen, and Visaltanachoti \(2018\)](#) study the link between politics and liquidity and find that U.S. financial markets are more liquid under Democrats as compared to Republicans. [Gulen and Ion \(2015\)](#) use the economic policy uncertainty index by [Baker, Bloom, and Davis \(2016\)](#) to show that investment falls due to policy uncertainty.

Market liquidity can be broadly defined as the ability of traders to execute large orders (buy side or sell side), without incurring high costs and without impacting the price too much or having to wait too long for the orders to get executed. It is a critical aspect of financial markets and has received extensive attention by researchers post the global financial crisis. [Brogaard, Li, and Xia \(2017\)](#) study the relationship between stock liquidity and default risk and find that enhanced stock liquidity can reduce default risk. [Chang, Chen, and Zolotoy \(2017\)](#) find that stock liquidity increases price crash risk. [Fang, Tian, and Tice \(2014\)](#) find that stock liquidity impedes firm innovation. Stock liquidity is also known to help reduce information asymmetry as it makes corporations increase dividend payouts which helps alleviate information asymmetry ([Jiang, Ma, and Shi \(2017\)](#)).

In this study, I plan to study the impact of political, economic policy and trade policy uncertainty on market liquidity and market efficiency. This study is related to several other studies that have looked at the connection between various kinds of uncertainties and their impact on market liquidity. [Rehse, Riordan, Rottke, and Zietz \(2019\)](#) study the impact of uncertainty arising as a result of Hurricane Sandy in a natural experiment setting (as the hurricane hit the New York area) on market liquidity. The results of [Rehse, Riordan, Rottke, and Zietz \(2019\)](#) show that bid-ask spreads widened as a result of the uncertainty arising from the hurricane.

[Glosten and Milgrom \(1985\)](#) offer a model where they postulate that the bid-ask spread which is essentially a measure of market liquidity arises due to the adverse selection costs faced by inventory holders. In an environment with higher political or economic policy uncertainty, there is a greater chance of loss when trading with an informed trader who might potentially have valuable information. This information asymmetry and the increased risk that it exposes the inventory holders to as a result of higher political or economic policy uncertainty leads to the widening of the bid-ask spread. This is one of the primary channels through which political or economic policy uncertainty affects stock liquidity.

It is evident from the discussion above that in general political uncertainty and economic policy uncertainty has material effect on financial outcomes. For example firms reduce investment during election year([Jens \(2017\)](#))and [Julio and Yook \(2012\)](#) find that firms lower their investment by 4.8 percent on average controlling for economic factors during election years. [Pástor and Veronesi \(2013\)](#) develop a model in which they postulate that due to concerns and uncertainty about the direction of future government policy and policy actions, stocks become more volatile and correlated. This theory is also confirmed by the empirical studies conducted by them in their study. Furthermore, in a study of German stocks [Bittlingmayer \(1998\)](#) also finds that political uncertainty leads to increase in stock volatility and decrease in output which is consistent with the evidence from the US. This added uncertainty and volatility of stock prices lends to the higher adverse selection costs which inventory holders offset by higher bid-ask spreads. This lack of certainty and clarity about the future direction of economic policy and political policy and the corresponding increase in stock volatility is an important channel through which political or economic policy uncertainty can affect stock liquidity.

The impact of higher volatility on market liquidity can be further explained using the market structure and liquidity model developed by [Grossman and Miller \(1988\)](#). The model explains how the demand for immediacy by sellers to receive a certain price for their security is met by market makers who offer a certain price immediately to the seller, but face an increased risk of a decline in price as the price is more volatile. To offset the higher risk that the market makers bare when they meet the sellers demand for immediacy, the market makers raise the bid-ask spread which reduces their risk to an extent but also reduces the stock liquidity. This is further proven by the model adapted by [Brunnermeier and Pedersen \(2008\)](#) who show that higher volatility leads to lower stock liquidity which in turn leads to flight to quality which sees investors shifting from less liquid to more liquid stocks.

[Duchin and Sosyura \(2012\)](#) provide further evidence that political connections are critical to obtain any form of funding from the government. Therefore, in times of political uncertainty the fate of firms with strong political connections is at stake because they receive preferential treatment from the government as exhibited by the studies cited above. [Acemoglu, Johnson, Kermani, Kwak, and Mitton \(2016\)](#) show that during the financial crises the financial firms linked to Timothy Geithner experienced cumulative abnormal returns in excess of 6 percent relative to non-linked financial firms. This clearly demonstrates that markets place great importance to political connections and in times of

political uncertainty these firms will face significant uncertainty as well and this is another mechanism through which stock liquidity will get impacted by political or economic policy uncertainty.

Jens (2017) rightly points out that one of the key issues in studying the impact of political uncertainty on financial markets is to separate the effect of political uncertainty from the effects of economic policy uncertainty and weaker economies. The reason for this difficulty as sighted by Jens (2017) is that an unexpected increase in political uncertainty is also strongly linked with an unexpected increase in economic policy uncertainty. Moreover, there is also a possibility that an increased period of economic policy uncertainty in fact leads to distrust in the government and hence increases political uncertainty as the government faces uncertainty over its political future. Liu, Shu, and Wei (2017) use the Bo scandal in China as an exogenous shock to political certainty and find that asset prices fell massively during the three days following the break out of the scandal. This approach of using the Bo scandal as an exogenous shock to political uncertainty allows us to overcome the issue of potentially confounding results due to the combined impact of economic policy, trade and political uncertainty. Therefore, I use the Bo scandal and adopt an event study methodology to study the impact of political uncertainty on stock liquidity.

We also use a news based and widely used policy uncertainty index to study the impact of policy uncertainty on liquidity. This policy uncertainty has been developed by Baker, Bloom, and Davis (2016). Gulen and Ion (2015) use the economic policy uncertainty index to study the impact of policy uncertainty on corporate investment and find that it severely inhibits corporate investment. Brogaard and Detzel (2015) find that economic policy uncertainty as measured by the Baker, Bloom, and Davis (2016) index is a good predictor of excess market returns. Kang and Ratti (2013) show that oil price shocks lead to increase in economic policy uncertainty which in turn reduce real stock returns. Hu, Kutan, and Sun (2018) show that US economic policy uncertainty is priced in Chinese A-shares market. Çolak, Gungoraydinoglu, and Öztekin (2018) show that increased economic policy uncertainty creates obstacles in a firm's attainment of optimal capital structure. Bhattacharya, Hsu, Tian, and Xu (2017) show that as a result of economic policy uncertainty during presidential election year, innovation activities are curtailed and fall to lows.

Davis, Liu, and Sheng (2019) also build an index on trade policy uncertainty on the lines of Baker, Bloom, and Davis (2016). Pierce and Schott (2016) suggests that the drop in US manufacturing related employment can be attributed to a US trade policy that lead

Figure 3.1: Economic Policy Uncertainty Index

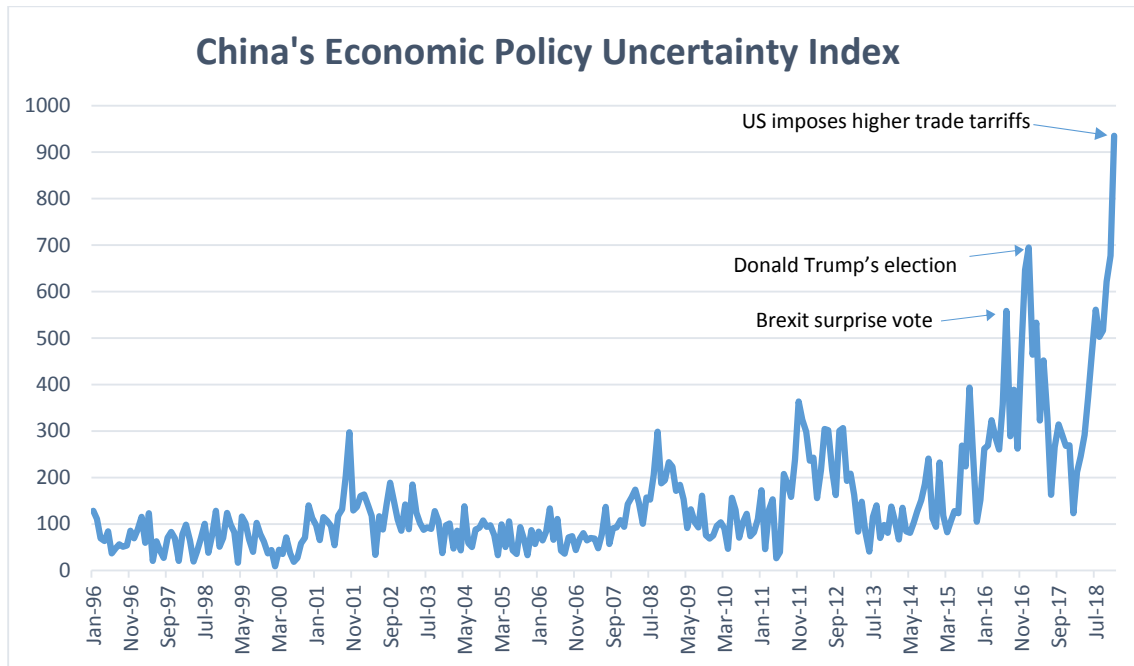


Figure 3.1: This graph shows the level of China's Economic policy uncertainty index developed by Baker, Bloom, and Davis (2016) from 1996 to 2018 which is our sample period. Key events that lead to huge spikes in the level of the index are marked in the figure.

to the elimination of a potential tariffs policy which further gave rise to increased Chinese imports. Handley and Limão (2017) study and model the US-China trade relationship and show that a decrease in trade policy uncertainty can bring increased aggregate welfare. Caliendo, Dvorkin, and Parro (2019) show that between 2000-2007, due to a rise in US-China trade, over half a million US manufacturing jobs were reduced. However, Caliendo, Dvorkin, and Parro (2019) show that the US gains in aggregate from trade. This conflicting evidence shows that trade tensions between the US and China are only going to escalate further and this will generate further trade policy linked uncertainty in the markets. These trade tensions are also a part of broader tensions between the two countries as evident from US naval ship exercises along the Taiwan Strait and disputed Chinese Islands. Therefore, these tensions have lead to increased geo-political tensions as well. ²

I use a panel regression methodology and event study methodology to study the impact of economic policy uncertainty, political uncertainty and trade policy uncertainty on stock liquidity as done in Beber and Pagano (2013) and Liu, Shu, and Wei (2017). Our

²See the Reuters news article :<https://www.reuters.com/article/us-usa-taiwan-china-military/two-us-navy-warships-sail-through-strategic-taiwan-strait-idUSKCN1S5003>

results indicate that economic policy uncertainty, political uncertainty and trade policy uncertainty all lead to an increase in illiquidity as measured by both our liquidity proxies the *HL* (High-Low spread) measure of (Corwin and Schultz, 2012) and the price impact *ILLIQ* measure of Amihud (2002). Moreover, as observed by Liu, Shu, and Wei (2017) the policy sensitive industries experience a bigger increase in spreads and also experience a bigger impact of political, economic policy and trade policy uncertainty. In addition to studying the impact of trade policy uncertainty on market liquidity, I also study the impact of trade policy uncertainty on market efficiency as I have high frequency data available for the period between April 1, 2016 and April 1, 2019 for the Chinese markets. The same cannot be done for the Bo scandal time period as Bloomberg has a limitation of storing high frequency data for only up to 180 days in the past. Therefore, purely due to data limitation, I only study the impact of political uncertainty on market liquidity, whereas, for trade policy uncertainty, I study the twin impacts on market liquidity as well as market efficiency.

The remainder of this paper is organized in four sections that follow. Section 3.2 discusses the development of our hypotheses. Section 3.3 discusses the data and methodology. Section 3.4 discusses the empirical results and finally Section 3.5 concludes the paper.

3.2 Hypotheses Development

Battalio and Schultz (2011) show that due to the regulatory uncertainty during the 2007-2008 financial crisis the bid-ask spread widened as well. The study most closely related to our study is Cox and Griffith (2018) that studies the impact of the uncertainty arising as a result of surprise Brexit referendum and Trump’s election as president on liquidity in financial markets. Our study is different from other studies as we take an exogenous shock in political uncertainty arising from the Bo scandal to study the impact of political uncertainty on market liquidity in an emerging market and our event was not previously priced in to the markets as both Brexit and Trump’s elections were already somewhat priced due to the presence of betting markets. Also, our study employs panel regressions as well as event study methodology and also uses the unique market structure of China’s stocks markets with A-shares, B-shares, State Owned Enterprises and Non State Owned Enterprises and measures of policy sensitiveness and political sensitivity to study the differential impact of these factors on stock liquidity.

Battalio and Schultz (2011) classify bid ask spreads in to three constituents. The first

constituent is the order processing cost, this is simply the compensation for exchange fees and other administrative costs incurred. The second constituent comprises the adverse selection costs, which is the cost of trading against more informed traders. The third and the most important constituent according to [Battalio and Schultz \(2011\)](#) is the inventory cost component. The inventory holding cost component of the bid-ask spread is most severely affected by regulatory uncertainty. In an environment of high information asymmetry, the market makers would have a target inventory holding position that is close to zero (so as to avoid any potential losses) due to unknown information or new unexpected information arriving in the market and hence, if they fill orders that deviates them from this zero net position target, due to risk aversion, they are likely to demand a higher bid-ask spread ([Battalio and Schultz \(2011\)](#)).

Moreover, there is a large part of the bid-ask spread which represents information asymmetry and volatility in prices. The dealers are expected to widen the bid ask spread to be compensated for adverse selection costs arising as a consequence of taking the other side of the market with potentially more informed traders ([Venkatesh and Chiang \(1986\)](#)). Intuitively, if there is greater economic policy uncertainty, trade policy uncertainty or political uncertainty, the bid-ask spread should widen even more due to an increased risk of losses arising from adverse selection.

This line of reasoning brings us to our three most important testable hypotheses:

Hypothesis 1: Higher political uncertainty should decrease liquidity and increase the transaction cost and price impact measures.

Hypothesis 2: Higher economic policy uncertainty should decrease liquidity and increase the transaction cost and price impact measures.

Hypothesis 3: Higher trade policy uncertainty should decrease liquidity and increase the transaction cost and price impact measures.

Furthermore, [Liu, Shu, and Wei \(2017\)](#) show that firms with higher policy sensitiveness experience a higher drop in stock prices in the three day event window surrounding the Bo political scandal in China. This demonstrates that there is a lot of panic selling and in such times the demand for liquidity goes up as liquidity becomes strained. Also, the likelihood of having a large price impact becomes higher. Under normal circumstances, to avoid a large price impact, traders place their orders out more evenly over larger periods of time. However, in case of an event all individual traders rush to sell their shares at the same time. This leads us to our next testable hypothesis:

Hypothesis 4: The impact of the political uncertainty and economic policy uncertainty

should be higher on more politically sensitive firms, these firms should experience a higher decrease in liquidity as the two uncertainties increase.

There is evidence from studies such as [Chordia, Roll, and Subrahmanyam \(2005\)](#) that larger firms are more liquid than smaller firms. More specifically in [Beber and Pagano \(2013\)](#) it is found that the impact of the short selling ban of 2008 in US and global financial markets hurt the smaller firms more in terms of liquidity. As the short selling ban essentially amounted to regulatory policy uncertainty, we therefore formulate our fifth testable hypothesis to reflect on the impact of our uncertainties in terms of size. Furthermore, [Liu, Shu, and Wei \(2017\)](#) also find that smaller firms experience a bigger drop in stock prices during the Bo political scandal.

Hypothesis 5: The impact of the political uncertainty, economic policy uncertainty and trade policy uncertainty should be higher on smaller firms, these firms should experience a higher decrease in liquidity as the two uncertainties increase.

Another unique feature of the Chinese stock market can be exploited as it has Class A-shares and Class B-shares. The two shares are issued for the same companies with identical cash flows and balance sheets. However, the ownership for two classes is different. Class A-shares are primarily held by domestic investors. Whereas, B-shares are held by foreign investors. Previous studies such as [Pan, Tang, and Xu \(2015\)](#) and [Kong, Lin, and Liu \(2017\)](#) claim that Class A-shares are owned by retail investors who lack sophistication and expertise and trade on noise. The general view is that institutional investors are more risk averse and are likely to trim their positions in large numbers and demand huge liquidity in the face of political crises([OConnell and Teo \(2009\)](#)). We now present our sixth testable hypothesis based on the difference in investor composition between A-shares and B-shares.

Hypothesis 6: The impact of the political uncertainty should be higher on Class B-shares as compared to their A-share counterparts in terms of liquidity due to majority of investors in B-shares being foreign institutional investors who are more risk averse.

China is also unique in that it still has a considerable number of state owned enterprises. [Liu, Shu, and Wei \(2017\)](#) study SOE directly owned by the central government and regress the cumulative abnormal returns on policy sensitiveness during the three day event window surrounding the Bo scandal and find that the coefficients on policy sensitiveness are less significant for SOE firms compared to non SOE firms. This suggests that policy sensitiveness is a bigger issue for non SOE firms. We now propose our seventh hypothesis to empirically test this difference between SOE and non SOE firms in greater detail.

Hypothesis 7: The impact of the political uncertainty should be higher on non SOE

firms as compared to SOE-firms in terms of liquidity due to the policy sensitiveness characteristics of the two firm classes.

3.3 Data

The data for this study is obtained from two main databases, China Stock Market and Accounting Research CSMAR and Bloomberg. The time period for this study extends from 1996 to 2018. Our sample consists of 3473 A-shares from all boards and exchanges of China. We also consider 88 dual listed B-shares during the 2012 Bo political scandal. The only exception to considering all firms is that for the political uncertainty event study of the Bo scandal of 2012, we consider the same sub-sample of firms considered by [Liu, Shu, and Wei \(2017\)](#). The sample of [Liu, Shu, and Wei \(2017\)](#) excludes all financial firms, firms that are not traded during the event window and the firms that lack necessary parameters and therefore a total of 1924 firms are considered by them.

The RRR policy announcement dates are collected from the People’s bank of China website and the total investment in fixed assets by province are obtained from China Statistical Yearbooks provided by the National Bureau of Statistics of China.³

The high frequency trade and quote data is extracted from Bloomberg for all exchanges and boards of China from April 2016 to April 2019. The number of firms is 3473 and includes only common stock. Various filters are applied to avoid inclusion of non common equity instruments such as exchange traded funds, debt instruments and preferred stocks. The stock ids are matched with stock ids from CSMAR and only stocks for which data is available on both are included.

We employ two of the most widely used measures of stock liquidity namely the bid-ask spreads as measured by the percentage quoted spread measured through the *HL* spread estimator ([Corwin and Schultz \(2012\)](#)) and the price impact *ILLIQ* ([Amihud \(2002\)](#)) measure. These two measures have the highest correlation with high frequency based liquidity measures as established by [Fong, Holden, and Trzcinka \(2017\)](#). This is also in line with other studies studying liquidity in the context of politics (see [Marshall, Nguyen, Nguyen, and Visaltanachoti \(2018\)](#)), regulatory uncertainty (see [Battalio and Schultz \(2011\)](#)), uncertainty arising from natural disasters and associated damage to financial markets and their infrastructure (see [Rehse, Riordan, Rottke, and Zietz \(2019\)](#)), short-sale ban and

³See the website :<http://www.stats.gov.cn/english/Statisticaldata/AnnualData/>

associated illiquidity (see [Beber and Pagano \(2013\)](#)).

3.3.1 *HL High Low Spread Proxy*

The High Low spread proxy is regarded as one of the most highly correlated proxy with effective spreads calculated from high frequency TAQ data for US markets and for various international markets ([Corwin and Schultz \(2012\)](#)). We lay out the formula used by [Corwin and Schultz \(2012\)](#) to estimate the High-Low (*HL*) spread proxy.

$$HL = \left(\frac{2(e^\alpha - 1)}{1 + e^\alpha} \right) \quad (3.1)$$

where:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \quad \beta = \sum_{i=0}^1 \left[\ln \left(\frac{H_{t+i}^0}{L_{t+i}^0} \right) \right]^2 \quad \gamma = \left[\ln \left(\frac{H_{t,t+1}^0}{L_{t,t+1}^0} \right) \right]^2 \quad (3.2)$$

HL is the High-Low spread estimator derived by [Corwin and Schultz \(2012\)](#), $H_{t,t+1}^0$ and $L_{t,t+1}^0$ are the high and low prices respectively over a single two day period. β is the function of the ratio of daily high and low prices over two consecutive days. γ is the function of the ratio of a single two day period with high and low prices over this single two day period.

The intuition behind this method of calculation of spread is that the high and low prices almost always represent the Ask and Bid prices respectively. Also, the volatility component of the high low price ratio increases proportionally over the time period considered, whereas, the spread component stays constant([Corwin and Schultz \(2012\)](#)).

Furthermore, in line with Section II [Corwin and Schultz \(2012\)](#) we make adjustment for overnight returns to obtain accurate spread estimates. For infrequently traded stocks, we use the daily high and low prices from a previous trading day in case of no trade on the current day or in case that the high and low prices are equal for a given day. In case, of negative estimates, the estimates are set to zero. Finally, we only consider estimates for which atleast 12 monthly observations are available.

3.3.2 *Amihud ILLIQ measure*

The *ILLIQ* ([Amihud \(2002\)](#)) measure looks at a different dimension of liquidity and rather than measuring transaction costs as in the *HL* ([Corwin and Schultz \(2012\)](#)) the High-Low spread estimator this is a measure of price impact. It is a measure of how much the price is sensitive to the dollar volume flowing in to the stock. The most basic premise

of a liquid market dictates that trades should be executed at optimal costs without causing a huge impact on prices.

Therefore, a higher measure of *ILLIQ* amounts to a higher price impact and hence, less liquidity.

$$ILLIQ = \frac{1}{D_{imy}} \sum_{t=1}^{D_{imy}} \frac{|R_{idmy}|}{RMBVOL_{idmy}} \quad (3.3)$$

ILLIQ is the monthly average stock Amihud (2002) illiquidity measure. D_{imy} is the number of the days that the stock trades for stock i , in month m for year y . $|R_{idmy}|$ is the absolute stock return for stock i , for day d , for month m for year y . $RMBVOL_{idmy}$ is the Chinese RMB value of all the trade volume executed in stock i , for day d , in month m for year y .

3.3.3 Effective Spread

The high frequency spread measure that we use for this research is the proportional effective spread as calculated by Abdi and Ranaldo (2017). This measure is linked to the transaction costs facet of stock liquidity.

$$ES_t = \frac{2 |P_t - M_t|}{M_t}, \quad M_t = \frac{A_t + B_t}{2} \quad (3.4)$$

P_t is the price at which the stock is traded at time t . M_t is the midpoint quote which is obtained by taking the average of the asking price A_t and the bid price B_t . The Chinese RMB weighted average of the effective spread is calculated for each day. This daily RMB weighted average is then averaged over the entire month to obtain a monthly measure.

3.4 Methodology

3.4.1 Liquidity and Political Uncertainty, Economic Policy Uncertainty and Trade Policy Uncertainty.

Our methodology focusses on testing our hypotheses outlined in the previous section. We begin by formulating regression equations that will test our Hypothesis 1, 2 and 3. We use the framework of Beber and Pagano (2013) who run an OLS regression with robust standard errors and control for firm fixed effects as liquidity tends to depend on them and ensure AR(1) correction as the spread is prone to autocorrelation.

$$HL_{i,m,y} = \alpha + \beta_1 EPU_{(m,y)} + \beta_2 Volatility_{(i,m,y)} + \epsilon_{(i,m,y)} \quad (3.5)$$

$HL_{i,m,y}$ is the High-Low (Corwin and Schultz (2012)) spread estimator for stock i , in month m for year y . $EPU_{m,y}$ is the economic policy uncertainty index (Baker, Bloom, and Davis (2016)) for month m in year y . $Volatility_{i,m,y}$ is the volatility of the stock i 's returns based on the standard deviation over the month m in year y .

$$ILLIQ_{i,m,y} = \alpha + \beta_1 EPU_{(m,y)} + \beta_2 Volatility_{(i,m,y)} + \epsilon_{(i,m,y)} \quad (3.6)$$

$ILLIQ_{i,m,y}$ is the Amihud (Amihud (2002)) price impact measure for stock i , in month m for year y . $EPU_{m,y}$ is the economic policy uncertainty index (Baker, Bloom, and Davis (2016)) for month m in year y . $Volatility_{i,m,y}$ is the volatility of the stock i 's returns based on the standard deviation over the month m in year y .

$$HL_{i,m,y} = \alpha + \beta_1 TPU_{(m,y)} + \beta_2 Volatility_{(i,m,y)} + \epsilon_{(i,m,y)} \quad (3.7)$$

$HL_{i,m,y}$ is the High-Low (Corwin and Schultz (2012)) spread estimator for stock i , in month m for year y . $TPU_{m,y}$ is the trade policy uncertainty index (Davis, Liu, and Sheng (2019)) for month m in year y . $Volatility_{i,m,y}$ is the volatility of the stock i 's returns based on the standard deviation over the month m in year y .

$$ILLIQ_{i,m,y} = \alpha + \beta_1 TPU_{(m,y)} + \beta_2 Volatility_{(i,m,y)} + \epsilon_{(i,m,y)} \quad (3.8)$$

$ILLIQ_{i,m,y}$ is the Amihud (Amihud (2002)) price impact measure for stock i , in month m for year y . $TPU_{m,y}$ is the trade policy uncertainty index (Davis, Liu, and Sheng (2019)) for month m in year y . $Volatility_{i,m,y}$ is the volatility of the stock i 's returns based on the standard deviation over the month m in year y .

To test our first hypothesis regarding the impact of political uncertainty on liquidity, we follow the methodology of Liu, Shu, and Wei (2017). We consider a three day event window from March 13-15, 2012 with March 14, 2012 being the day when the Bo political scandal broke out in China. The advantage of this event study regression approach is that we are able to segregate the impact of political uncertainty from other potential uncertainties and the dates are in a tight range of when the brunt of the scandal's impact hit the markets as demonstrated by Liu, Shu, and Wei (2017). This approach ensures that the results are not influenced by other factors and is advocated by Beber and Pagano (2013).

$$HL_{i,event} = \alpha + \beta_1 PA_{(i,event)} + \beta_2 LnFV_{(i,event)} + \beta_3 BM_{(i,event)} + \beta_4 LAGHL_{(i,event)} + \beta_5 IdVol_{(i,m,y)} + \beta_6 LEV_{(i,event)} + \epsilon_{(i,event)} \quad (3.9)$$

$$HL_{i,event} = \alpha + \beta_1 FI_{(i,event)} + \beta_2 LnFV_{(i,event)} + \beta_3 BM_{(i,event)} + \beta_4 LAGHL_{(i,event)} + \beta_5 IdVol_{(i,m,y)} + \beta_6 LEV_{(i,event)} + \epsilon_{(i,event)} \quad (3.10)$$

$HL_{i,event}$ is the High-Low (Corwin and Schultz (2012)) spread estimator for stock i during the 3 day *event* period March 13-15, 2012 with March 14, 2012 being the day when the Bo political scandal broke out in China. $PA_{(i,event)}$ is the policy announcement measure as calculated by Liu, Shu, and Wei (2017) for firm i during the Bo political scandal event period. The value of this measure ranges from 0 to 1, with 1 indicating the highest level of sensitiveness to policy announcements. $FI_{(i,event)}$ is the fixed investment measure as calculated by Liu, Shu, and Wei (2017) for firm i during the Bo political scandal event period. The value of this measure range from 0 to 1, with 1 indicating the highest level of sensitiveness to fixed investment from the government. $LnFV_{(i,event)}$ is the logarithmic market value of stock i one week prior to the *event* (Bo Political Scandal). $BM_{(i,event)}$ is the ratio of the Book to Market value of stock i one week prior to the *event* (Bo Political Scandal). $LAGHL_{(i,event)}$ is the average of the high low estimator for the period from two weeks to one week prior to the Bo political scandal event break out. $LEV_{(i,event)}$ is the leverage of the firm i defined as the ratio of total liabilities to total assets. $IdVol_{(i,event)}$ is obtained as per Liu, Shu, and Wei (2017).

$$ILLIQ_{i,event} = \alpha + \beta_1 PA_{(i,event)} + \beta_2 LnFV_{(i,event)} + \beta_3 BM_{(i,event)} + \beta_4 LAGILLIQ_{(i,event)} + \beta_5 IdVol_{(i,m,y)} + \beta_6 LEV_{(i,event)} + \epsilon_{(i,event)} \quad (3.11)$$

$$ILLIQ_{i,event} = \alpha + \beta_1 FI_{(i,event)} + \beta_2 LnFV_{(i,event)} + \beta_3 BM_{(i,event)} + \beta_4 LAGILLIQ_{(i,event)} + \beta_5 IdVol_{(i,m,y)} + \beta_6 LEV_{(i,event)} + \epsilon_{(i,event)} \quad (3.12)$$

$ILLIQ_{i,event}$ is the Amihud (Amihud (2002)) price impact for stock i during the *event* which is the 3 day period March 13-15, 2012 with March 14, 2012 being the day when the Bo political scandal broke out in China. $PA_{(i,event)}$ is the policy sensitivity measure policy announcement as calculated by Liu, Shu, and Wei (2017) for firm i during the Bo political scandal event period. The value of this measure ranges from 0 to 1, with 1 indicating the

highest level of sensitiveness to policy announcements. $FI_{(i,event)}$ is the fixed investment measure as calculated by Liu, Shu, and Wei (2017) for firm i during the Bo political scandal event period. The value of this measure range from 0 to 1, with 1 indicating the highest level of sensitiveness to fixed investment from the government. $LnFV_{(i,event)}$ is the logarithmic market value of stock i one week prior to the *event* (Bo Political Scandal). The value of this measure ranges from 0 to 1, with 1 indicating the highest level of sensitiveness to policy announcements. $BM_{(i,event)}$ is the ratio of the Book to Market value of stock i one week prior to the *event* (Bo Political Scandal). $LAGHL_{(i,event)}$ is the average of the high low estimator for the period from two weeks to one week prior to the Bo political scandal event break out. $LEV_{(i,event)}$ is the leverage of the firm i defined as the ratio of total liabilities to total assets. $IdVol_{(i,event)}$ is obtained as per Liu, Shu, and Wei (2017).

3.4.2 Efficiency and Trade Policy Uncertainty

We then focus our attention on the impact of a tweet by US President on March 2, 2018 claiming that trade wars are ‘easy to win’ which marked the beginning of the trade war between the US and China and has been followed by months and months of uncertainty regarding the outcome of tariffs from either sides. ⁴

Using high frequency data we test for the impact of an exogenous shock to trade policy as a consequence of this unexpected imposition of US tariffs on Chinese goods on market efficiency. This is done using the return predictability framework of Chordia, Roll, and Subrahmanyam (2005) and Rösch, Subrahmanyam, and Van Dijk (2016). Moreover, we use the variance ratio tests based on Rösch, Subrahmanyam, and Van Dijk (2016) as well for this purpose.

In our first specification the Variance ratio is defined as:

$$\frac{\widehat{\text{Var}}_{30mins}[s]}{\widehat{\text{Var}}_{1min}[s]} \quad (3.13)$$

Where, the numerator is the scaled variance of a 30 minute period return in each 30 minute daily interval s . The denominator is the scaled variance of a 1 minute period return in each in each 30 minute daily interval s .

In our first specification the Variance ratio is defined as:

$$\frac{\widehat{\text{Var}}_{5mins}[s]}{\widehat{\text{Var}}_{15sec}[s]} \quad (3.14)$$

⁴The CNBC report is available at: <https://www.cnbc.com/2019/06/29/us-china-trade-talks-at-g-20-timeline-of-how-the-tariff-war-started.html>

Where, the numerator is the scaled variance of a 5 minute period return in each 30 minute daily interval s . The denominator is the scaled variance of a 15 second period return in each 30 minute daily interval s .

For random walk to prevail, the following should be true- a) $\text{Var}(30 \text{ minutes}) = 30 * \text{Var}(1 \text{ minute})$ and for the second variance ratio test, b) $\text{Var}(5 \text{ minutes}) = 20 * \text{Var}(15 \text{ seconds})$ and this would ensure that the ratio of the two variances converges to unity.

The return predictability framework is adapted from [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) where returns for intervals ranging from 1 minute to 15 minute are considered.

$$\text{Returns}_{i,t} = \alpha_{i,t} + \beta_{1,i,t} \text{Returns}_{i,t-1} + \beta_{2,i,t} \text{OINUM}_{i,t-1} + \epsilon_{i,t} \quad (3.15)$$

$$\text{Returns}_{i,t} = \alpha_{i,t} + \beta_{1,i,t} \text{Returns}_{i,t-1} + \beta_{2,i,t} \text{OIVAL}_{i,t-1} + \epsilon_{i,t} \quad (3.16)$$

Where $\text{Returns}_{i,t}$ is the mid quote return associated with stock i during the interval t . $\text{OINUM}_{i,t-1}$ is the lagged order imbalance in terms of the number of buyer trades exceeding number of seller trades classified as per the algorithm by [Lee and Ready \(1991\)](#) associated with stock i during the preceding time interval $t - 1$. $\text{OIVAL}_{i,t-1}$ is the lagged order imbalance calculated as the Chinese RMB value of buyer sides trades exceeding the value of seller side trades again classified as per the algorithm by [Lee and Ready \(1991\)](#) associated with stock i over the immediately preceding time interval $t - 1$. This is done using the event study regression framework of [Chang, Luo, and Ren \(2014\)](#). They use a period of 180 days prior and post 31 days of the event occurrence date to capture the impact of the event on market efficiency.

3.5 Empirical Results

3.5.1 Descriptive Evidence on Impact of Political Uncertainty on Liquidity.

We begin by providing descriptive evidence in Table [3.2](#) on the role of political uncertainty in elevating transaction costs as measured by the HL High-Low ([Corwin and Schultz \(2012\)](#)) spread estimator. We study our entire set of firms based on the sector that they belong to. Using the policy sensitivity measure *PolicyAnnouncement* based on [Liu, Shu, and Wei \(2017\)](#) to rank the sectors in order of increasing policy sensitivity we

find that the most sensitive sectors experience the largest increases in spreads during the Bo Political scandal.

Also, the spreads of the most policy sensitive sectors remain elevated for the 50 day post event period. The Wilcoxon test is employed based on [Beber and Pagano \(2013\)](#) which tests for the statistical difference between the medians between the three sub periods-pre-scandal, during the scandal and post-scandal indicates that the difference in medians is statistically significant at the 1% level. The more policy sensitive sectors as outlined in Table 3.1 experience a bigger increase in *HL* High-Low ([Corwin and Schultz \(2012\)](#)) spread measures in the 3 day window surrounding the Bo scandal as compared to the average of the 50 day period pre and post the Bo scandal. Moreover, we observe that the spreads remain larger in the post event period particularly for the Finance and Real Estate sector. On the contrary, the least policy sensitive sectors such as IT and Manufacturing sectors return to near pre-political crisis levels.

3.5.2 Economic Policy Uncertainty and Illiquidity: Regression Analysis

We now turn to an OLS panel regression investigation to test our hypothesis regarding the adverse impact of economic policy uncertainty on liquidity. Our hypothesis predicted that higher economic policy uncertainty should lead to lower(higher) liquidity(illiquidity). In line with [Beber and Pagano \(2013\)](#) we control for firm level fixed effects which control for factors affecting liquidity such as analyst coverage, available float etc. An important determinant of the bid-ask spread is the volatility of a stock as explained by [Battalio and Schultz \(2011\)](#) and also employed as a control variable by [Beber and Pagano \(2013\)](#). We control for volatility as well in our regression analyses.

Moreover, we also control for autocorrelation in spreads as they are typically correlated ([Beber and Pagano \(2013\)](#)). In addition to these controls, we also control for stock volatility in our regression. In Panel A, column 1 of Table 3.3 we present the regression estimates for the entire sample. The dependent variable is the *HL* High-Low ([Corwin and Schultz \(2012\)](#)) spread. The independent variable is the monthly index value of economic policy uncertainty ([Baker, Bloom, and Davis \(2016\)](#)). The estimate in column 1 of Table 3.3 is positive and significant which indicates that there is a positive relation between economic policy uncertainty and illiquidity.

In Table 3.3 Panel A, column 2 we take a sample of Financial stocks and perform the same regression analysis that we did in column 1. The coefficient estimate for the *EPU*

economic policy uncertainty index ([Baker, Bloom, and Davis \(2016\)](#)) is still significant, and stronger than column 1. The estimate for *EPU* in column 1 is 5.76(raw estimate), 0.23 (standardized coefficient) with t-statistics of 20.31, while that in column 2 is 6.13 (raw estimate), 0.25 (standardized coefficient) with a t-statistic of 15.52 owing to the fewer number of observations. In terms of standardized coefficients, 1 standard deviation in *EPU* causes 0.23 standard deviations in the sample of all stocks. However, for financial stocks 1 standard deviation in *EPU* causes 0.25 standard deviations. These results demonstrate how policy sensitiveness plays a vital role in driving spreads owing to policy uncertainty. The results are in line with our expectation that more policy sensitive sectors should experience a larger gain in spreads owing to economic policy uncertainty.

In Table 3.3 Panel A, column 3 we take a sample of Real Estate stocks and perform the same regression analysis that we did in column 1. The raw and standardized estimate of the regression coefficient on *EPU* is close in economic and statistical significance to that in column 2 where we had considered a sample of Financial stocks. Since both the sectors considered are sectors with high political sensitivity, we conclude that sectors with higher policy sensitivity exhibit a higher sensitivity to economic policy uncertainty in terms of their spreads. Furthermore, the positive sign of the raw and standardized coefficients suggest that higher policy sensitivity and higher *EPU* both lead to higher transaction costs.

To further ensure that our results are not driven solely by policy sensitive sectors and to differentiate between highly policy sensitive sectors and less policy sensitive sectors we also consider regressions with only the IT sector and Manufacturing firms in columns 4 and 5 respectively. We see that the standardized regression coefficient estimates of the *HL* High-Low ([Corwin and Schultz \(2012\)](#)) spread on *EPU* are relatively lower for IT and Manufacturing firms as compared to the more policy sensitive sectors -Financials and Real Estate.

In an effort to further determine the impact of economic policy uncertainty on the non-financial and non-real estate sector, we run regressions in column 6. We note that the standardized regression coefficient estimate of *HL* on *EPU* are smaller than column 1 which included the financial and real estate sectors. However, the estimates are still significant at the 1% level. The estimates are however, lower than the estimates in column 1. This further confirms that policy sensitivity plays a significant role in driving spreads during periods of increased economic policy uncertainty as the regression coefficients of sectors with higher policy sensitivity as measured by *PolicyAnnouncement* based on [Liu](#),

Shu, and Wei (2017) exhibit higher economic and statistical significance.

We now turn our attention to Table 3.3 Panel B. In Panel B, our dependent variable is the *ILLIQ* (Amihud (2002)) price impact measure. The observations made in Panel A are applicable to Panel B as well. Panel B also serves as a robustness test to our initial analyses which looks at a different facet of liquidity-price impact. As in Panel A, we note that the standardized regression coefficient estimate of *ILLIQ* on *EPU* is highest for column 2 (all financials) and column 3 (real estate firms) which are highly policy sensitive sectors as per the *PolicyAnnouncement* measure based on Liu, Shu, and Wei (2017). Whereas, it is lower for less policy sensitive sectors like IT and Manufacturing as evident in Panel B columns 4 and 5 respectively. This provides further evidence that even using a different measure of liquidity namely *ILLIQ* our results in Panel A still hold. We can therefore conclude that the relationship between liquidity and *EPU* is not limited to just one specification or dimension of stock liquidity, but impacts two most important dimensions and hence our findings are robust to multiple definitions of liquidity.

Therefore, based on the standardized regression coefficients of *HL* and *ILLIQ* regressed on *EPU*, we can conclude that the *HL* measure is affected more by *EPU* than *ILLIQ*. However, there is consistency in *EPU* explaining a greater level of change in both *HL* and *ILLIQ* for more policy sensitive sectors like the financial and real estate sectors.

3.5.3 Economic Policy Uncertainty, Liquidity and Size

It has been previously established that owing to higher liquidity larger firms exhibit higher market efficiency (see Chordia, Roll, and Subrahmanyam (2005), Chordia, Roll, and Subrahmanyam (2008)), while smaller firms even in normal conditions (without elevated uncertainties) experience liquidity issues. Also, market makers consider small market capitalization stocks as being riskier and are hesitant to provide liquidity in these stocks (see Beber and Pagano (2013) and references therein). Therefore, we can hypothesize that economic policy uncertainty should have a greater impact on smaller stocks. To test our hypothesis we now turn our attention to study the difference in impact of economic policy uncertainty on liquidity for small versus large stocks.

An OLS panel regression will be employed similar to the one employed by (Beber and Pagano (2013)) and earlier in our study in Section 3.5.2. We control for firm level fixed effects, AR(1) correlation and volatility as done earlier and justified. We divide the sample of firms each year in to four quartiles by size of market capitalization at the beginning of each year.

The regression results are reported in Table 3.4. In Panel A, column 1 of Table 3.4 we present the regression estimates for the smallest firm (lowest market capitalisation) quartile. In Panel A, the dependent variable is the *HL* High-Low (Corwin and Schultz (2012)) spread. The independent variable is *EPU* (the monthly index value) economic policy uncertainty measure (Baker, Bloom, and Davis (2016)). The regression estimates are highest in column 1 for the regression of *HL* on *EPU*. We see that as we move from column 1 to column 4, as the size of the firms keeps getting larger, the regression coefficient estimates keep getting smaller and less statistically significant. This shows that smaller firms are more prone to economic policy uncertainty and their spreads are more highly affected by such uncertainty relative to larger firms. This is also true due to various financing constraints that smaller firms face in China as the official financial system is reluctant in giving loans to them (Allen, Qian, Tu, and Yu (2019)). In times of political uncertainty it becomes further more difficult for these smaller firms to operate and it increases uncertainty concerning their future.

In Table 3.4 Panel B, the regression results are reported for the dependent variable which is the *ILLIQ* (Amihud (2002)) price impact measure on the independent variable which is *EPU* (the monthly index value) economic policy uncertainty measure (Baker, Bloom, and Davis (2016)). As seen in Panel A, we note that the coefficient estimates are strongest and most statistically significant for column 1 (which has the smallest firms sorted by size quartile). As we move from column 1 to column 4 (which has the largest firms by size quartile) we note that the coefficient estimates get smaller from column 1 estimates of 6.02(raw estimate), 0.22 (standardized coefficient) and t-statistics of 15.36 to column 4 with an estimate of 5.19(raw estimate), 0.17(standardized coefficient) and t-statistics of 11.02. We interpret the standardized coefficients and find that in the lowest size quartile, one standard deviation in *EPU* will cause 0.22 standard deviations in the *ILLIQ* measure. Whereas, for the highest size quartile, one standard deviation in *EPU* will cause 0.17 standard deviation in *ILLIQ*. We also note that the estimates also get less statistically significant as we move from the lowest to the highest size quartile. This further confirms our finding that smaller firms are more prone to economic policy uncertainty in terms of not just their spreads, but also their price impact measure.

3.5.4 Political Uncertainty and Liquidity

We now turn to the event study regression methodology as employed by Liu, Shu, and Wei (2017). We run two separate regressions. In Panel A, *HL* High-Low (Corwin and

Schultz (2012)) spread is the dependent variable regressed on the independent variable policy sensitivity measure *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) in column 1 and column 2 of Table 3.5. Whereas, in Panel B, the dependent variable is switched to another liquidity measure, *ILLIQ* (Amihud (2002)) price impact measure.

The other control variables are firm specific, *LnFV* and *BM* are logarithmic value of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGHL* is the lagged *HL* average measure for the period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). The regression t-statistics are robust to standard errors clustered by industry and province where the firms are incorporated.

In Panel A Table 3.5, we note that the regression estimates of *HL* High-Low (Corwin and Schultz (2012)) spread on the *Policy – announcement* measure is 0.22 (standardized coefficient), 0.331 (raw estimate) and (t-statistic= 3.12) which is significant at the 1% level. Also, the coefficient estimate in column 2, Panel A, of *HL* regressed on *Fixed – investment* is 0.26 (standardized coefficient), 0.986 (raw estimate) (t-statistic= 4.36). Our results indicate that both the measures of political uncertainty *Policy – announcement* and *Fixed – investment* have a negative impact on transaction costs as they have a positive and significant coefficient.

In Panel A, the standardized regression coefficient of *HL* on *Fixed – investment* is higher than the standardized regression coefficient on *Policy – announcement*. This indicates that firm’s that are incorporated in provinces highly sensitive to government investment are affected less by political uncertainty than firms that are more sensitive to monetary policy announcements made by the government. This further highlights the importance and the role of government in driving the dynamics of firms in China.

In Panel B Table 3.5, we consider an alternate specification of liquidity which is the *ILLIQ* (Amihud (2002)) price impact measure. Our findings indicate that the findings in Panel A, hold with the alternate liquidity measure as well. It serves as a robustness test and proves that our findings are not subject to any particular definition or dimension of liquidity. In Panel B as well, we see that the standardized regression coefficient estimates for column 2 which are 0.30 with *Fixed – investment* as the independent variable are higher than those for column 1 which is 0.28. This again re-enforces the findings in

Panel. Therefore, the liquidity of firms are more sensitive to *Fixed – investment* policy sensitivity measure . Moreover, as observed in Panel A, the regression estimates on both policy sensitiveness measures are significant at 1% level.

We now turn our attention to the raw and standardized regression coefficient estimates of the control variables to gain further insights on how firm specific variables can influence the impact of political uncertainty on the firm. The negative and significant estimates on *LnFV* (the logarithm of the firm value) and *BM* (book to market ratio) indicate that political uncertainty impacts the liquidity of small firms more than larger firms. In simpler terms, a higher firm value leads to lower transaction costs. Also, the liquidity of firms with a higher book to market ratio is less affected by political uncertainty. This shows that smaller firms and low book to market value stocks which are growth stocks (with a low book to market ratio) are the ones most hard hit during political uncertainty and crises and more specifically during the 3 day event window around the Bo political scandal in China from March 13 to March 15, 2012. These findings make intuitive sense because studies like (Chordia, Roll, and Subrahmanyam, 2005) suggest that smaller firms are more susceptible to higher information asymmetry and stock volatility (Beber and Pagano (2013)) a result of market or regulatory uncertainty.

Furthermore, the regression estimates on *LEV* (leverage) which is the ratio of the total assets to the total liabilities of the firm and *IdVOL* (idiosyncratic volatility) are positive and significant. The standardized coefficient is larger for *LEV* as compared to *IdVOL*. This positive regression coefficients show that firms with higher leverage and higher idiosyncratic volatility are also likely to suffer more in terms of their liquidity in times of political uncertainty and particularly during the 3 day event window surrounding the Bo political scandal in China. These findings are not surprising since leverage increases the uncertainty regarding economic outcomes of a firm and contributes to overall information asymmetry which is a key predictor of liquidity costs.

3.5.5 Political Uncertainty and Liquidity: SOE versus non SOE enterprises

Liu, Shu, and Wei (2017) find that abnormal returns of non SOE enterprises during the Bo political scandal show greater sensitivity to policy sensitiveness measures. We therefore, segregate the sample in to SOE and non SOE enterprises to study the difference in impact of the political scandal on the liquidity of SOE versus non SOE firms. Our Hypothesis 7 specifically predicted that political uncertainty should impact the liquidity of SOE firms

less significantly than non-SOE firms. This is also supported by the arguments provided by [Liu, Shu, and Wei \(2017\)](#) who state that regardless of what government comes to power, the economic policy is going to be designed to benefit SOE firms since they are owned by the government. On the other hand, [Liu, Shu, and Wei \(2017\)](#) argue that non-SOE firms are more independent and vulnerable to changes in economic policy and therefore, should suffer greater in terms of liquidity during times of heightened economic policy uncertainty.

We now turn to the event study regression methodology as employed by [Liu, Shu, and Wei \(2017\)](#) by segregating the sample in to SOE versus non SOE firms. We run two separate regressions. In Panel A, we consider 952 SOE firms in which *HL* High-Low ([Corwin and Schultz \(2012\)](#)) spread is the dependent variable regressed on the independent variable policy sensitivity measure *Policy – announcement* and *Fixed – investment* as per [Liu, Shu, and Wei \(2017\)](#) in column 1 and column 2 of Table 3.6. In Panel B, we consider 972 non-SOE firms in which *HL* High-Low ([Corwin and Schultz \(2012\)](#)) spread is the dependent variable regressed on the independent variable policy sensitivity measure *Policy – announcement* and *Fixed – investment* as per [Liu, Shu, and Wei \(2017\)](#) in column 1 and column 2 of Table 3.6.

LnFV and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio respectively measured one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGHL* is the lagged *HL* average measure for the period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in [Liu, Shu, and Wei \(2017\)](#). The regression t-statistics are robust to standard errors clustered by industry and province where the firms are incorporated.

Our findings indicate that the regression estimate in Panel A of *HL* on *Policy – announcement* is 0.16(standardized coefficient) and 0.253 (raw estimate) (t-statistic= 2.31) and is significant at the 5% level. Whereas, in Panel B, the regression estimate of *HL* regressed on *Policy – announcement* is 0.26(standardized coefficient) and 0.521(t-statistic= 3.87) which is significant at 1% level. These findings indicate that the bid-ask spreads of SOE firms are less sensitive to political uncertainty as compared to non SOE firms. This is again due to the argument that regardless of whoever comes in to power and whatever policy is made by that government it will always be pro-government and pro-SOE ([Liu, Shu, and Wei \(2017\)](#)). Whereas, the flip side of the argument by [Liu, Shu, and Wei \(2017\)](#) is that the non-SOE firms are independent and more susceptible to policy

uncertainty whims of the government.

In column 2, we regress *HL* High-Low (Corwin and Schultz (2012)) spread on the *Fixed – investment* as calculated in Liu, Shu, and Wei (2017) measure. In Panel A, where we consider SOE firms, the regression estimate of *HL* regressed on *Fixed – investment* is 0.15 (standardized coefficient) and 0.82(t-statistic= 2.16) which is significant at 5% level. Whereas, in Panel B, where we consider non SOE firms, the regression estimate of *HL* regressed on *Fixed – investment* is 0.31(standardized coefficient) and 1.14(t-statistic= 4.84) which is significant at 1% level. This further establishes that during the 3 day event window around the Bo Political scandal the impact of political sensitiveness on the bid-ask spreads of non SOEs was higher than the impact of political sensitiveness on SOEs. This is also particularly interesting since the *Fixed – investment* measure is based on the amount that the government investments in each province where the firms are located and is the ratio of government investment to total investment for that region. Given the role of government in China, it is logical to anticipate that non-SOE firms would be highly sensitive to the investment made by the government in their region of operation because that would also drive the broader economic environment and market conditions. Also, regardless of whatever government comes in to power, the SOE firms are going to be shielded as the government would continue to form policies that benefit itself (Liu, Shu, and Wei (2017)).

In Table 3.7, we consider the same regression as in Table 3.6. However, rather than taking *HL* High-Low (Corwin and Schultz (2012)) spread as the dependent variable, we take *ILLIQ* (Amihud (2002)) price impact measure as the dependent variable. The other independent variables and control variables are identical to the regression in Table 3.6. This also serves as a robustness test for our findings in Table 3.6 as we consider an alternative definition of liquidity by using a different dimension of liquidity which is price impact rather than just relying on findings based on transaction costs.

In column 1 of Panel A, Table 3.7, we regress *ILLIQ* (Amihud (2002)) price impact measure on the *Policy – announcement* measure as calculated in Liu, Shu, and Wei (2017). In Panel A, where we consider SOE firms, the regression estimate of *ILLIQ* on *Policy – announcement* is 0.24(standardized coefficient) and 0.456(t-statistic= 3.85) which is significant at 1% level. Whereas, in Panel B, where we consider non SOE firms, the regression estimate of *ILLIQ* regressed on *Policy – announcement* is 0.30 (standardized coefficient) and 0.498(t-statistic= 4.56) which is significant at 1% level. We note that as seen in Table 3.6 in the case of transaction costs, the SOE firms are less sensitive to

political uncertainty as compared to non SOE firms in terms of their price impact as well. We note that the price impact measure is impacted more so by both measures of political uncertainty and SOE firms still exhibit a lower sensitivity to non-SOE firms however, the effect is significant at 1% level for both SOE and non-SOE firms.

We now run the same regression as in Panel A, but with a different policy sensitiveness measure- *Fixed – investment*. Our findings in Panel A(SOE firms) indicate that the regression estimate in column 2 of Table 3.7 of *ILLIQ* (Amihud (2002)) price impact measure on *Fixed – investment* is 0.25(standardized coefficient) and 0.92 (t-statistic= 4.21) and is significant at the 1% level. Whereas, column 2, in Panel B (non SOE firms), we obtain the regression estimate of *ILLIQ* (Amihud (2002)) price impact measure on *Fixed – investment* as 0.31(standardized coefficient) and 1.15(t-statistic= 4.63) which is significant at 1% level. Again as we saw in the case of transaction costs, the price impact measure is also more sensitive to political uncertainty measures in non-SOE firms as compared to SOE firms. This directly follows from the fact that non-SOE firms had a higher sensitiveness to the political uncertainty measures in terms of their abnormal returns during the eruption of the Bo scandal as documented by Liu, Shu, and Wei (2017). Since investors trade higher volumes on better performing stocks(Chordia, Goyal, and Jegadeesh (2016)), we see that this is one channel through which the market liquidity of non-SOE firms suffers more during a political crisis.

There are other reasons to support the relatively milder impact of political uncertainty on SOE firms versus non-SOE firms. Allen, Qian, Tu, and Yu (2019) show that SOE firms receive lower interest rates on loans versus their non-SOE counterparts. It is factors like these that actually insulate SOE firms from various political and policy related uncertainties.

3.5.6 Political Uncertainty and Liquidity: Dual listed A-Shares versus B-Shares

We now wish to exploit yet another unique feature of Chinese stock markets which is the existence of dual listed A-shares and B-shares. Dual listed A-shares and B-shares are stocks of the same firms with similar cash flows, balance sheets, voting rights etcetera. However, the distinction between is the investor composition. Dual listed A-shares are primarily held by retail investors, whereas, the dual listed B-shares are primarily held by institutional investors. OConnell and Teo (2009) develop a model and show that institutional investors are likely to be more risk averse as they need to report their financial performance. They

are also likely to be slow to add positions during price increases and swift to reverse positions during losses (OConnell and Teo (2009)). Our results in this section support the theory of OConnell and Teo (2009) as we see that dual listed B-shares are prone to more sensitivity to political uncertainty as compared to their A-listed counterparts. Moreover, there is also evidence of flight to home effect in times of crises by foreign entities (Giannetti and Laeven (2012)).

We run our regression in Equation 3.9 and Equation 3.10. In these equations the dependent variable is the *HL* High-Low (Corwin and Schultz (2012)) spread and the dependent variables are the *Policy – announcement* measure and *Fixed – investment* policy sensitiveness measures respectively. The other control variables are the same as those used in Section 3.5.5 and are explained therein.

Table 3.8, Panel A, reports the results of regressions in Equation 3.9 and Equation 3.10 for the sub-sample of dual listed A-shares in column 1 and column 2 respectively. We note that the regression coefficient of *HL* on *Policy – announcement* is which is 0.24(standardized coefficient) and 0.486 (t-statistic= 3.51) is significant at 1% level. We note that the regression coefficient of *HL* on *Fixed – investment* is 0.28 (standardized coefficient) and 0.92 (t-statistic= 4.61) which is is significant at 1% level. Panel B, reports the results of regressions in Equation 3.9 and Equation 3.10 for the sub-sample of dual listed B-shares in column 1 and column 2 respectively. We note that the regression coefficient of *HL* on *Policy – announcement* is 0.26 (standardized coefficient) and 0.500 (t-statistic= 3.62) which is is significant at 1% level. We note that the regression coefficient of *HL* on *Fixed – investment* is 0.31(standardized coefficient) and 1.05 (t-statistic= 4.73) which is is significant at 1% level. The results in Table 3.8 indicate that spreads of dual listed B-shares are more sensitive to political uncertainty as compared to the sensitivity of dual listed A-shares to political uncertainty.

To check the robustness of our findings we consider an alternative definition of liquidity-*ILLIQ* (Amihud (2002)) price impact measure as the dependent variable and run the regressions in Equation 3.11 and Equation 3.12. Our findings in Table 3.9 indicate that as seen in Table 3.8, the liquidity of the dual listed class A-shares in Panel A exhibits smaller and less statistically significant estimates on *Policy – announcement* of 0.24(standardized coefficient) and 0.492(t-statistic=3.21) whereas, in Panel B the estimates on *Policy – announcement* are 0.26(standardized coefficient) and 0.503(t-statistic= 3.39). For the other policy sensitiveness measure *Fixed – investment* also the estimates in Panel A are 0.24(standardized coefficient) and 1.01(t-statistic=3.44) whereas, in Panel B they are

0.29 (standardized coefficient) and 1.06(t-statistic= 3.58) . These results further prove that regardless of the definition of both the liquidity measure or the policy sensitiveness measure, the dual listed class B-shares exhibit greater sensitivity to political uncertainty as compared to their class A-share dual listed counterparts. Since, the only difference between both the share classes is their investor composition, we conclude that foreign institutional investors of class B-shares are more risk averse as also demonstrated by (OConnell and Teo (2009)). In the wake of the political crisis during the Bo scandal and in general they demonstrate the flight to safety effect consistent with Giannetti and Laeven (2012) and thereby, reduce the liquidity of B-shares.

3.5.7 Trade Policy Uncertainty and Liquidity

After having considered the impact of economic policy uncertainty and political uncertainty on liquidity. We now turn our focus to studying the impact of trade policy uncertainty on liquidity. We employ the regression methodology of Beber and Pagano (2013) and conduct an OLS panel regression as per Equation 3.7. We control for firm level fixed effects, volatility and employ robust standard errors clustered at the firm level.

Our findings outlined in column 1(all sector sample) Table 3.10 demonstrate that the coefficient of *HL* (Corwin and Schultz (2012)) spread on *TPU* (Davis, Liu, and Sheng (2019)) trade policy uncertainty index is 6.25 (t-statistic= 22.36) which is significant at 1% level. In contrast to the findings observed for the coefficient estimate of *HL* on *EPU* we note that the coefficient estimates on *TPU* are highest in column 5, 6.45(t-statistic=20.74), which is the manufacturing sector sample. Whereas, in case of regression of *HL* on *EPU* the estimate was highest for the real estate sector, in case of the regression of *HL* on *TPU*, real estate sector shows the smallest coefficient, 5.29 (t-statistic=13.89). This indicates that while economic policy uncertainty impacts the real estate the most, trade policy uncertainty impacts it the least.

3.5.8 Trade Policy Uncertainty and Liquidity: The Impact of Size

We now study the impact of trade policy uncertainty on liquidity by segregating the sample in to quartiles based on market capitalization of the firms. An OLS panel regression will be employed similar to the one employed by (Beber and Pagano (2013)) and earlier in our study in Section 3.5.3.

Our results in column 1(Lowest size quartile) Table 3.11 indicate that the regression coefficient of *HL* (Corwin and Schultz (2012)) spread on *TPU* (Davis, Liu, and Sheng

(2019)) trade policy uncertainty index is 5.35 (t-statistic= 10.36) which is significant at 1% level. We note that as we go from column 1 to column 4 to higher size quartiles, the coefficients become smaller and less statistically significant. The coefficient of regression estimates in column 4 is 6.58(t-statistic=13.25). This shows that the spreads of larger firms are more sensitive to trade policy uncertainty as compared to smaller firms. We note that this finding is in contrast to the findings in Section 3.5.3 in which we found that the spreads of smaller firms are more sensitive to economic policy uncertainty. This is due to the greater export sensitivity of large global firms relative to smaller firms(Bernard, Jensen, Redding, and Schott (2018)).

3.5.9 Trade Policy Uncertainty and Market Efficiency

We now study the impact of trade policy uncertainty on another important feature of stock markets- market efficiency. Chordia, Roll, and Subrahmanyam (2008) prove that liquidity plays an important role in determining market efficiency. We therefore, expect that since trade policy uncertainty decreases liquidity, it should also lead to reduced market efficiency. We use an exogenous shock to trade policy uncertainty when President Donald Trump tweeted on March 2,2018 that trade wars were ‘easy to win’ and gave jitters to the markets.⁵ This has been followed by a series of tariffs and retaliatory tariffs and has caused the Chinese markets to be among the worst performers in the world in 2018. ⁶

Following the regression framework of Chang, Luo, and Ren (2014), we use a period of 180 days prior and post 31 days of the event occurrence date to capture the impact of the event on market efficiency. So our dates of interest for both the return predictability measure and variance ratio measures are 1st August, 2017 to 1st February, 2018 which is the pre-event window to the post-event window which is 3rd April, 2018 to 3rd October, 2018.

In Table 3.12 the variance ratios are reported for all 8 half hour intervals from 9:30 - 11:30 am and from 1:00 pm to 3:00 pm of each trading day are reported for the pre and post-event window are reported. We report both variance ratio specifications -the 15 second to 5 minute ratios and for the 1 minute to 30 minute ratios. We note that across all 8 half hour intervals during each trading day, both the variance ratios are closer to unity in the pre-event window as compared to the post event window. This makes us conclude

⁵The CNBC report is available at:<https://www.cnbc.com/2019/06/29/us-china-trade-talks-at-g-20-timeline-of-how-the-tariff-war-started.html>

⁶The BBC report is available at:<https://www.cnbc.com/2019/06/29/us-china-trade-talks-at-g-20-timeline-of-how-the-tariff-war-started.html>

that the imposition of tariffs and the trade-war between the U.S. and China has lead to the deterioration of market efficiency.

In Table 3.13, we report the results for the intraday return predictability regressions as in Equation 3.15 and Equation 3.16, where we consider two time windows- pre-event and post-event window from 1st August, 2017 to 1st February, 2018 and 3rd April, 2018 to 3rd October, 2018 respectively. We note that in terms of return predictability in Equation 3.15 and Equation 3.16, at the one minute interval, the pre-event coefficient estimates on $OINUM_{t-1}$ are 0.92(t-statistic= 3.93) and on $OIVAL_{t-1}$ are 0.231(t-statistic=3.98). Whereas, at the one minute interval, the post event estimates on $OINUM_{t-1}$ are 0.97(t-statistic= 4.13) and on $OIVAL_{t-1}$ are 2.45 (t-statistic=4.17). Therefore, we notice that the regression estimates on both $OINUM_{t-1}$ and $OIVAL_{t-1}$ are higher and more significant in the post event window in comparison to the pre event window and are indicative of lower market efficiency post-event.

We now turn our attention to other intervals of interest- the two, three, five and ten minute intervals. We note that across all these intervals there is an increase in both the regression coefficients on $OINUM_{t-1}$ and $OIVAL_{t-1}$ in the post-event window compared to the pre-event window as reported in Table 3.13. Furthermore, we notice that as the intervals of interest increase in size from one minute to ten minutes, the regression estimates experience a decline, in both the pre and post event windows. This is consistent with the notion that return predictability becomes smaller with time as arbitrageurs exploit any inefficiency and the market converges towards efficiency (Chordia, Roll, and Subrahmanyam (2005)).

3.6 Conclusion

This study provides evidence that indicates that economic policy uncertainty, political uncertainty, trade policy uncertainty are detrimental to liquidity. Furthermore, our results that use high frequency intraday data show that trade policy uncertainty impedes market efficiency to a great extent. We reach these conclusions using a panel regression and an event study regression methodology as employed by Beber and Pagano (2013), Liu, Shu, and Wei (2017) and Chang, Luo, and Ren (2014) respectively.

We conclude that sectors exhibiting greater policy sensitiveness experience a larger increase in their transaction costs during the Bo political scandal. Also, the transaction costs of more policy sensitive sectors are more sensitive to economic policy uncertainty

as measured by the economic policy uncertainty index ([Baker, Bloom, and Davis \(2016\)](#)). We also find that economic policy uncertainty affects small firms more than large firms. In terms of political uncertainty, the liquidity of SOEs is less impacted by policy sensitiveness measures as compared to non SOE firms. This shows that private sector firms have more to lose during political uncertainty as compared to state owned enterprises.

Our findings in terms of liquidity and trade policy uncertainty indicate that the manufacturing sector is most highly impacted by trade policy uncertainty which is contrary to the case of economic policy uncertainty which impacts the financial and real estate sectors the most. Furthermore, we show that following the break out of the trade war between the US and China, market efficiency has suffered as indicated by both the return predictability measure and the variance ratio measure which are both very widely used measures of market efficiency as also used by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#).

We are able to demonstrate that three different types of uncertainties can impact market liquidity and market efficiency. This study contributes to the studies that discuss the potential impact of political and economic policy uncertainty on stocks. In the current environment when the trade war between the US and China in particular and the US and the rest of the world is of primary concern, it is a very timely study that contributes to understanding the implications of trade policy uncertainty in terms of a very important factor in the markets which is liquidity.

Table 3.1: Summary Statistics

This table reports the sector wise summary of the main variables used in this research. *HL* is the mean value of the High Low estimator for transaction costs ([Corwin and Schultz, 2012](#)) estimated sector wise for the entire sample period. It also reports the average of the policy sensitiveness measure across all firms in that specific industry based on [Liu, Shu, and Wei \(2017\)](#) for the time period ranging from 1996-2018.

Sector	Number of stocks	<i>HL</i>	Policy sensitiveness
IT	264	0.322	0.336
Manufacturing	2266	0.369	0.345
Hotels/Catering	10	0.397	0.356
Public Health	10	0.293	0.385
Education	6	0.315	0.392
Research and Development	52	0.342	0.397
Construction	96	0.387	0.410
Business Support	53	0.394	0.412
Media	59	0.388	0.422
Environmental Protection	49	0.356	0.452
Agriculture	42	0.321	0.458
Wholesale and Retail	166	0.303	0.459
Utilities	109	0.280	0.465
Transportation	101	0.341	0.487
Conglomerates	22	0.373	0.501
Mining	76	0.402	0.520
Finance	86	0.361	0.552
Real Estate	130	0.354	0.601

Table 3.2: Mean High Low Spreads and the Political Scandal

This table reports the number of stocks in each industry sector for the Chinese stock market. It also reports the average of the policy sensitiveness measure across all firms in that specific industry based on [Liu, Shu, and Wei \(2017\)](#). *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Sector	<i>HL</i> High Low Spread		
	50 Day Window		
	Before Scandal	During Scandal	After Scandal
IT	0.318	0.434***	0.360
Manufacturing	0.371	0.499***	0.385
Hotels/Catering	0.455	0.519***	0.499
Public Health	0.291	0.414***	0.320
Education	0.305	0.342***	0.321
Research and Development	0.336	0.382***	0.342
Construction	0.413	0.443***	0.420
Business Support	0.443	0.485***	0.456
Media	0.422	0.571***	0.426
Environmental Protection	0.362	0.431***	0.371
Agriculture	0.344	0.515***	0.405
Wholesale and Retail	0.299	0.506***	0.390
Utilities	0.223	0.560***	0.480
Transportation	0.342	0.404***	0.385
Conglomerates	0.366	0.518***	0.485
Mining	0.390	0.555***	0.505
Finance	0.349	0.549***	0.525
Real Estate	0.335	0.562***	0.541

Table 3.3: Transaction Costs, Price Impact and Economic Policy Uncertainty:Regression Analysis

The table reports the regression results for the multivariate regression of the *HL* (Corwin and Schultz (2012)) monthly High Low spread measure of transaction costs on EPU(monthly Economic Policy Uncertainty Index) based on Baker, Bloom, and Davis (2016) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month in Panel A. In Panel B, the dependent variable is the *ILLIQ* (Amihud (2002))the monthly average price impact measure and EPU(monthly Economic Policy Uncertainty Index) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month as independent variables. The regression is further controlled for stock level fixed effects and AR(1) correction is carried out in line with Beber and Pagano (2013). The co-efficients of EPU in Panel A are scaled by 10^5 whereas in Panel B, the coefficients of Constant, EPU and Volatility are scaled by 10^9 for inclusion and presentation purposes. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: *HL* (High Low Spread as Dependent Variable)

Sector	(1) (All)	(2) (Financials)	(3) (Real Estate)	(4) (IT)	(5) (Manufacturing)	(6) (Ex-Fin/RE)
<i>Constant</i>	0.131*** (214.61)	0.127*** (200.33)	0.126*** (202.52)	0.120*** (170.82)	0.114*** (180.53)	0.121*** (196.65)
<i>EPU</i>	5.76*** (20.31) 0.23	6.13*** (15.52) 0.25	6.29*** (17.19) 0.26	5.09*** (16.23) 0.21	5.15*** (18.96) 0.24	5.31*** (18.23) 0.21
<i>Volatility</i>	1.24*** (45.68) 0.32	1.26*** (35.69) 0.36	1.29*** (38.76) 0.32	1.22*** (31.25) 0.28	1.23*** (35.26) 0.30	1.23*** (34.89) 0.30
Stock level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	500,220	12,387	18,724	38,024	326,374	469,109

Panel B: *ILLIQ* (Price Impact as Dependent Variable)

Sector	(1) (All)	(2) (Financials)	(3) (Real Estate)	(4) (IT)	(5) (Manufacturing)	(6) (Ex-Fin/RE)
<i>Constant</i>	5.12*** (14.42)	5.17*** (12.89)	5.13*** (13.39)	5.02*** (10.36)	4.95*** (10.89)	4.86*** (12.55)
<i>EPU</i>	5.44*** (17.28) 0.19	5.87*** (12.48) 0.21	5.98*** (14.14) 0.22	5.06*** (13.18) 0.17	5.15*** (15.78) 0.19	5.23*** (16.18) 0.18
<i>Volatility</i>	4.08*** (21.69) 0.23	4.35*** (15.69) 0.25	4.48*** (16.81) 0.26	4.59*** (14.25) 0.23	4.54*** (20.37) 0.28	4.59*** (20.59) 0.29
Stock level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	500,220	12,387	18,724	38,024	326,374	469,109

**Table 3.4: Transaction Costs, Price Impact and Economic Policy
Uncertainty: Impact of Size**

The table reports the regression results for the multivariate regression of the *HL* (Corwin and Schultz (2012)) monthly High Low spread measure of transaction costs on EPU(monthly Economic Policy Uncertainty Index) based on Baker, Bloom, and Davis (2016) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month in Panel A. In Panel B, the dependent variable is the *ILLIQ* (Amihud (2002))the monthly average price impact measure and EPU(monthly Economic Policy Uncertainty Index) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month as independent variables. The regression is further controlled for stock level fixed effects and AR(1) correction is carried out in line with Beber and Pagano (2013). The firms are divided in to size quartiles based on the market capitalisation at the beginning of each year. The co-efficients of EPU in Panel A are scaled by 10^5 whereas in Panel B, the coefficients of Constant, EPU and Volatility are scaled by 10^9 for inclusion and presentation purposes. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: <i>HL</i> (Transaction Cost as Dependent Variable)				
Size Quartile	(1) (Lowest)	(2)	(3)	(4) (Highest)
<i>Constant</i>	0.123*** (102.23)	0.126*** (105.68)	0.132*** (112.52)	0.139*** (120.96)
<i>EPU</i>	8.23*** (15.32) 0.24	7.12*** (13.39) 0.20	6.01*** (11.63) 0.18	5.09*** (10.75) 0.17
<i>Volatility</i>	1.36*** (26.68) 0.35	1.23*** (25.54) 0.29	1.15*** (22.36) 0.26	1.08*** (21.26) 0.23
Stock level fixed effects	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes
No. of observations	125,052	125,056	125,052	125,056
Panel B: <i>ILLIQ</i> (Price Impact as Dependent Variable)				
Sector	(1) (Lowest)	(2)	(3)	(4) (Highest)
<i>Constant</i>	5.56*** (15.32)	5.31*** (13.41)	5.15*** (12.24)	4.92*** (10.86)
<i>EPU</i>	6.02*** (15.36) 0.22	5.84*** (13.53) 0.20	5.46*** (12.26) 0.18	5.19*** (11.02) 0.17
<i>Volatility</i>	4.83*** (17.24) 0.28	4.58*** (13.58) 0.25	4.31*** (12.12) 0.23	4.13*** (10.73) 0.21
Stock level fixed effects	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes
No. of observations	125,052	125,056	125,052	125,056

Table 3.5: Impact of the Bo scandal on Transaction Costs and Price Impact

The table reports regression results with dependent variable *HL* (Corwin and Schultz (2012)) which is the three-day average for the Bo scandal event window(March 13-15) of High Low spread measure of transaction costs in Panel A. The independent variables are policy sensitiveness measures *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) and demonstrate the impact of policy sensitiveness on transaction costs. In Panel B, dependent variable is the *ILLIQ* (Amihud (2002))the three day average price impact measure for the Bo scandal event window(March 13-15) is regressed on policy sensitiveness measures *Policy – announcement* and *Fixed – investment* calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017) and demonstrates the impact of policy sensitiveness on price impact. The other control variables are firm specific, *LnFV* and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGHL* is the lagged *HL* average measure for the a period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal whereas,*LAGILLIQ* is the lagged *ILLIQ* parameter calculated in a similar manner. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). The t-statistics are reported in parentheses below the co-efficient and are robust to standard errors clustered by industry and province. All coefficients in Panel B are scaled by 10^6 for inclusion and presentation purposes. *, ** and ***denote statistical significance at 10%, 5% and 1% respectively.In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: <i>HL</i> (Transaction Costs as Dependent Variable)		
	(1)	(2)
<i>Policy – announcement</i>	0.331*** (3.12) 0.22	
<i>Fixed – investment</i>		0.986*** (4.36) 0.26
<i>LnFV</i>	-0.216*** (-4.68) -0.28	-0.211*** (-4.53) -0.26
<i>BM</i>	-1.19*** (-5.29) -0.29	-1.26*** (-5.35) -0.30
<i>LEV</i>	0.82*** (3.26) 0.24	0.86*** (3.28) 0.25
<i>LAGHL</i>	0.266*** (4.23) 0.22	0.268*** (4.29) 0.23
<i>IdVOL</i>	0.314*** (3.21) 0.18	0.316*** (3.23) 0.19
<i>INTERCEPT</i>	1.03*** (5.63)	1.06*** (5.71)
No. of firms/observations	1924	1924

(Continued)

Table 3.5 – *Continued*

Panel B: <i>ILLIQ</i> (Price Impact as Dependent Variable)		
	(1)	(2)
<i>Policy – announcement</i>	0.475*** (3.86) 0.28	
<i>Fixed – investment</i>		1.02*** (4.79) 0.30
<i>LnFV</i>	−0.563*** (−4.85) −0.31	−0.574*** (−4.92) −0.28
<i>BM</i>	−0.365*** (−3.36) −0.29	−0.379*** (−3.57) −0.30
<i>LEV</i>	0.423*** (3.69) 0.27	0.447*** (3.88) 0.29
<i>LAGILLIQ</i>	0.325*** (3.66) 0.36	0.328*** (3.72) 0.37
<i>IdVOL</i>	0.456*** (4.13) 0.23	0.478*** (4.26) 0.24
<i>INTERCEPT</i>	1.11*** (3.33)	1.16*** (3.37)

Table 3.6: Impact of the Bo Scandal on Transaction Costs: SOE versus non SOE Regression Analysis

The table reports regression results with dependent variable *HL* (Corwin and Schultz (2012)) which is the three-day average for the Bo scandal event window(March 13-15) of High Low spread measure of transaction costs in Panel A for SOE stocks. The independent variables are policy sensitiveness measures *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) and demonstrate the impact of policy sensitiveness on transaction costs. In Panel B, non SOE stocks are taken. The other control variables are firm specific, *LnFV* and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGHL* is the lagged *HL* average measure for the a period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). The t-statistics are reported in parentheses below the co-efficient and are robust to standard errors clustered by industry and province. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: SOE firms		
	(1)	(2)
<i>Policy – announcement</i>	0.253** (2.25) 0.16	
<i>Fixed – investment</i>		0.82** (2.16) 0.15
<i>LnFV</i>	−0.202*** (−3.35) −0.23	−0.191*** (−3.42) −0.24
<i>BM</i>	−1.02*** (−3.89) −0.25	−0.92*** (−4.02) −0.26
<i>LEV</i>	0.72*** (3.06) 0.20	0.75*** (3.08) 0.21
<i>LAGHL</i>	0.262*** (3.52) 0.20	0.265*** (3.55) 0.20
<i>IdVOL</i>	0.302*** (3.05) 0.15	0.305*** (3.08) 0.16
<i>INTERCEPT</i>	1.02*** (3.38)	1.04*** (3.41)
No. of firms/observations	952	952

(Continued)

Table 3.6 – *Continued*

Panel B: Non SOE firms		
	(1)	(2)
<i>Policy – announcement</i>	0.521*** (3.87) 0.26	
<i>Fixed – investment</i>		1.14*** (4.84) 0.31
<i>LnFV</i>	–0.231*** (–4.85) –0.30	–0.220*** (–4.62) –0.28
<i>BM</i>	–1.16*** (–5.51) –0.31	–1.06*** (–5.39) –0.32
<i>LEV</i>	0.89*** (3.59) 0.27	0.93*** (3.75) 0.29
<i>LAGHL</i>	0.269*** (4.29) 0.26	0.272*** (4.36) 0.27
<i>IdVOL</i>	0.320*** (3.45) 0.20	0.327*** (3.51) 0.21
<i>INTERCEPT</i>	1.05*** (5.65)	1.08*** (5.74)
No. of firms/observations	972	972

Table 3.7: Impact of the Bo scandal on Price Impact: SOE versus non SOE Regression Analysis

The table reports regression results with dependent variable *ILLIQ* (Amihud (2002)) which is the three-day average for the Bo scandal event window(March 13-15) of price impact in Panel A for SOE stocks. The independent variables are policy sensitiveness measures *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) and demonstrate the impact of policy sensitiveness on transaction costs. In Panel B, non SOE stocks are taken. The other control variables are firm specific, *LnFV* and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGILLIQ* is the lagged *ILLIQ* average measure for the a period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). All coefficients are scaled by 10^6 for inclusion and presentation purposes. The t-statistics are reported in parentheses below the co-efficient and are robust to standard errors clustered by industry and province. *, **and ***denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: SOE Firms		
	(1)	(2)
<i>Policy – announcement</i>	0.456*** (3.85) 0.24	
<i>Fixed – investment</i>		0.92*** (4.21) 0.25
<i>LnFV</i>	−0.551*** (−4.72) −0.28	−0.563*** (−4.79) −0.29
<i>BM</i>	−0.351*** (−3.22) −0.24	−0.363*** (−3.45) −0.26
<i>LEV</i>	0.405*** (3.29) 0.25	0.422*** (3.37) 0.27
<i>LAGILLIQ</i>	0.314*** (3.59) 0.32	0.320*** (3.63) 0.33
<i>IdVOL</i>	0.448*** (3.79) 0.20	0.469*** (4.06) 0.21
<i>INTERCEPT</i>	1.03*** (3.25)	1.09*** (3.31)
No. of firms/observations	1924	1924

(Continued)

Table 3.7 – *Continued*

Panel B: Non SOE Firms		
	(1)	(2)
<i>Policy – announcement</i>	0.498*** (4.56) 0.30	
<i>Fixed – investment</i>		1.15*** (4.63) 0.31
<i>LnFV</i>	–0.575*** (–5.03) –0.34	–0.591*** (–5.24) –0.32
<i>BM</i>	–0.376*** (–3.36) –0.30	–0.384*** (–3.42) –0.32
<i>LEV</i>	0.437*** (3.78) 0.31	0.459*** (3.96) 0.33
<i>LAGILLIQ</i>	0.340*** (3.74) 0.35	0.348*** (3.85) 0.36
<i>IdVOL</i>	0.463*** (4.25) 0.23	0.486*** (4.48) 0.22
<i>INTERCEPT</i>	1.15*** (3.45)	1.21*** (3.52)
No. of firms/observations	1924	1924

Table 3.8: Impact of the Bo scandal on Transaction Costs: Dual Listed Shares

The table reports regression results with dependent variable *HL* (Corwin and Schultz (2012)) which is the three-day average for the Bo scandal event window(March 13-15) of High Low spread measure of transaction costs in Panel A for dual listed A-Shares. The independent variables are policy sensitiveness measures *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) and demonstrate the impact of policy sensitiveness on transaction costs. In Panel B, dual listed B-Shares are taken. The other control variables are firm specific, *LnFV* and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGHL* is the lagged *HL* average measure for the a period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal, . *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). The t-statistics are reported in parentheses below the co-efficient and are robust to standard errors clustered by industry and province. *, **and ***denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: Dual listed shares listed as A-Shares		
	(1)	(2)
<i>Policy – announcement</i>	0.486*** (3.51) 0.24	
<i>Fixed – investment</i>		0.92*** (4.61) 0.28
<i>LnFV</i>	−0.220*** (−3.67) −0.20	−0.214*** (−3.52) −0.19
<i>BM</i>	−1.17*** (−4.23) −0.21	−1.24*** (−4.36) −0.23
<i>LEV</i>	0.81*** (3.13) 0.22	0.87*** (3.24) 0.23
<i>LAGHL</i>	0.255*** (3.47) 0.20	0.258*** (3.52) 0.21
<i>IdVOL</i>	0.326*** 0.17	0.333*** 0.19
<i>INTERCEPT</i>	1.04*** (4.36)	1.09*** (4.51)
No. of firms/observations	88	88

(Continued)

Table 3.8 – *Continued*

Panel B: Dual listed shares listed as B-Shares		
	(1)	(2)
<i>Policy – announcement</i>	0.500*** (3.62) 0.26	
<i>Fixed – investment</i>		1.05*** (4.73) 0.31
<i>LnFV</i>	–0.225*** (–3.80) –0.22	–0.218*** (–3.65) –0.20
<i>BM</i>	–1.21*** (–4.36) –0.24	–1.29*** (–4.49) –0.25
<i>LEV</i>	0.85*** (3.29) 0.25	0.90*** (3.44) 0.26
<i>LAGHL</i>	0.262*** (3.62) 0.21	0.268*** (3.75) 0.22
<i>IdVOL</i>	0.331*** (3.52) 0.20	0.342*** (3.63) 0.21
<i>INTERCEPT</i>	1.04*** (4.36)	1.09*** (4.51)
No. of firms/observations	88	88

Table 3.9: Impact of the Bo scandal on Price Impact: Dual Listed Shares

The table reports regression results with dependent variable *ILLIQ* (Amihud (2002)) which is the three-day average for the Bo scandal event window(March 13-15) of price impact in Panel A for dual listed A-Shares. The independent variables are policy sensitiveness measures *Policy – announcement* and *Fixed – investment* as per Liu, Shu, and Wei (2017) and demonstrate the impact of policy sensitiveness on transaction costs. In Panel B, dual listed B-Shares are taken. The other control variables are firm specific, *LnFV* and *BM* are logarithmic values of the firm’s market capitalization and its book to market ratio one week prior to the eruption of the scandal. *LEV* is the total assets to total liabilities ratio for each stock. *LAGILLIQ* is the lagged *ILLIQ* average measure for the a period of one week ranging from the period two weeks to just one week prior to the eruption of the scandal. *IdVOL* is Idiosyncratic stock volatility calculated as per Table 3 and Appendix C in Liu, Shu, and Wei (2017). All coefficients are scaled by 10^6 for inclusion and presentation purposes. The t-statistics are reported in parentheses below the co-efficient and are robust to standard errors clustered by industry and province. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Panel A: Dual listed A-Shares		
	(1)	(2)
<i>Policy – announcement</i>	0.492*** (3.21) 0.24	
<i>Fixed – investment</i>		1.01*** (3.44) 0.27
<i>LnFV</i>	−0.553*** (−3.74) −0.29	−0.575*** (−3.96) −0.31
<i>BM</i>	−0.365*** (−3.36) −0.25	−0.371*** (−3.43) −0.24
<i>LEV</i>	0.421*** (3.45) 0.29	0.429*** (3.54) 0.30
<i>LAGILLIQ</i>	0.329*** (3.45) 0.32	0.333*** (3.54) 0.33
<i>IdVOL</i>	0.456*** (3.41) 0.22	0.466*** (3.50) 0.23
<i>INTERCEPT</i>	1.09*** (3.20)	1.14*** (3.27)
No. of firms/observations	88	88

(Continued)

Table 3.9 – *Continued*

Panel B: Dual listed B- Shares		
	(1)	(2)
<i>Policy – announcement</i>	0.503*** (3.39) 0.26	
<i>Fixed – investment</i>		1.06*** (3.58) 0.29
<i>LnFV</i>	−0.562*** (−3.86) −0.32	−0.581*** (−4.01) −0.34
<i>BM</i>	−0.372*** (−3.42) −0.27	−0.379*** (−3.51) −0.28
<i>LEV</i>	0.428*** (3.52) 0.31	0.431*** (3.63) 0.32
<i>LAGILLIQ</i>	0.335*** (3.52) 0.35	0.342*** (3.65) 0.36
<i>IdVOL</i>	0.459*** (3.58) 0.23	0.471*** (3.74) 0.25
<i>INTERCEPT</i>	1.11*** (3.23)	1.18*** (3.31)
No. of firms/observations	88	88

**Table 3.10: Transaction Costs and Trade Policy Uncertainty:
Regression Analysis**

The table reports the regression results for the multivariate regression of the *HL* (Corwin and Schultz (2012)) monthly High Low spread measure of transaction costs on TPU(monthly Trade Policy Uncertainty Index) based on Davis, Liu, and Sheng (2019) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month in Panel A. In Panel B, the dependent variable is the *ILLIQ* (Amihud (2002))the monthly average price impact measure and TPU(monthly Trade Policy Uncertainty Index) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month as independent variables. The regression is further controlled for stock level fixed effects and AR(1) correction is carried out in line with Beber and Pagano (2013). The co-efficients of EPU in Panel A are scaled by 10^5 . *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Sector	(1) (All)	(2) (Financials)	(3) (Real Estate)	(4) (IT)	(5) (Manufacturing)	(6) (Ex-Fin/RE)
<i>Constant</i>	0.130*** (209.45)	0.135*** (212.33)	0.132*** (210.48)	0.125*** (180.61)	0.123*** (201.48)	0.128*** (206.98)
<i>TPU</i>	6.25*** (22.36) 0.30	5.78*** (14.63) 0.26	5.29*** (13.89) 0.25	6.09*** (17.56) 0.29	6.45*** (20.74) 0.30	6.31*** (17.92) 0.31
<i>Volatility</i>	1.31*** (50.23) 0.45	1.22*** (42.61) 0.41	1.24*** (35.58) 0.34	1.25*** (37.25) 0.36	1.21*** (39.22) 0.38	1.22*** (33.54) 0.32
Stock level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	500,220	12,387	18,724	38,024	326,374	469,109

Table 3.11: Transaction Costs and Trade Policy Uncertainty: Impact of Size

The table reports the regression results for the multivariate regression of the *HL* (Corwin and Schultz (2012)) monthly High Low spread measure of transaction costs on TPU(monthly Trade Policy Uncertainty Index) based on Davis, Liu, and Sheng (2019) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month in Panel A. In Panel B, the dependent variable is the *ILLIQ* (Amihud (2002))the monthly average price impact measure and TPU(monthly Trade Policy Uncertainty Index) and Volatility (stock volatility) as measured by the moving average of the standard deviation of the returns over the month as independent variables. The regression is further controlled for stock level fixed effects and AR(1) correction is carried out in line with Beber and Pagano (2013). The firms are divided in to size quartiles based on the market capitalisation at the beginning of each year. The co-efficients of EPU in Panel A are scaled by 10^5 . *, ** and *** denote statistical significance at 10%, 5% and 1% respectively. In the first row for each variable the regression coefficient is reported, in the second row the corresponding t-statistics are reported and in the third row the standardized coefficient is reported.

Size Quartile	(1) (Lowest)	(2)	(3)	(4) (Highest)
<i>Constant</i>	0.135*** (115.94)	0.132*** (112.39)	0.130*** (109.45)	0.125*** (107.96)
<i>TPU</i>	5.35*** (10.36) 0.25	6.15*** (11.19) 0.26	6.39*** (12.14) 0.27	6.58*** (13.25) 0.29
<i>Volatility</i>	1.25*** (25.36) 0.48	1.21*** (24.42) 0.43	1.20*** (22.64) 0.40	1.19*** (20.26) 0.35
Stock level fixed effects	Yes	Yes	Yes	Yes
AR(1) Correction	Yes	Yes	Yes	Yes
No. of observations	125,052	125,056	125,052	125,056

Table 3.12 : Variance Ratio Tests for the Impact of U.S Imposed Tariffs

The sample consists of all Chinese stocks listed on Shanghai and Shenzhen stock exchanges. The combined number of A-shares listed on them is 3473 for the pre-event window 1st August, 2017 to 1st February, 2018 and the post event window extending from 3rd April, 2018 to 3rd October, 2018. For each half hour interval (for each firm), we calculate variance ratios based on 15 second and 5 minute mid-quote returns. The first row in the table reports time series averages of the cross sectional averages of these variance ratios. The time series average of the cross sectional standard deviation is in parentheses. The intervals are numbered from 1 to 4, for each half hour interval between 9:30 am and 11:30 am for the pre lunch session, and for the post lunch session the intervals are numbered from 5 to 8 for the time interval between 1:00 pm to 3:00 pm. The first interval 1 represents the time period from 9:30-10:00 am, interval 2 represents the time period from 10:00-10:30 am, interval 3 represents the time interval from 10:30- 11:00 am and so on until interval 8 represents 2:30-3:00 pm.

Trade Tariffs	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event Window								
15 sec to 5 min	1.05 (0.43)	1.03 (0.41)	1.02 (0.41)	1.03 (0.42)	1.03 (0.41)	1.02 (0.40)	1.02 (0.41)	1.03 (0.42)
Post-Event Window								
15 sec to 5 min	1.06 (0.44)	1.04 (0.41)	1.03 (0.42)	1.04 (0.43)	1.04 (0.43)	1.02 (0.42)	1.02 (0.41)	1.03 (0.43)
Trade Tariffs	Time intervals							
	1	2	3	4	5	6	7	8
Pre-Event window								
1 min to 30 min	1.03 (0.40)	1.02 (0.39)	1.02 (0.39)	1.03 (0.40)	1.03 (0.40)	1.02 (0.39)	1.02 (0.38)	1.03 (0.39)
Post-Event window								
1 min to 30 min	1.05 (0.43)	1.04 (0.42)	1.03 (0.41)	1.04 (0.42)	1.04 (0.42)	1.03 (0.41)	1.02 (0.40)	1.03 (0.42)

Table 3.13 : Multivariate Regressions for the Impact of Trade Tariffs

Midpoint returns and order imbalances are obtained as defined in the variable definitions. Bloomberg is used to access data for stocks that trade on Shanghai and Shenzhen stock markets. The sample consists of all Chinese stocks listed on Shanghai and Shenzhen stock exchanges. The combined number of A-shares listed on them is 3473 for the the pre-event window 1st August, 2017 to 1st February, 2018 and the post event window extending from 3rd April, 2018 to 3rd October, 2018. This ensures that we drop the 31 days immediately preceding the event as recommended by [Chang, Cheng, and Yu \(2007\)](#) and also adopted by [Chang, Luo, and Ren \(2014\)](#). The dependent variable is the return in the current interval and it is regressed in two separate regressions on $Return_{t-1}$ and $OINUM_{t-1}$ as well as on $Return_{t-1}$ and $OIVAL_{t-1}$ respectively. A stock level regression is run for each stock and the cross sectional means of individual stock regressions is reported as in [Chordia, Roll, and Subrahmanyam \(2005\)](#). The average t-statistic from the individual stock regressions is reported in the second row and is enclosed in parentheses. Finally the t-statistic computed by adjusting for cross-correlation in the residuals is reported in the third row. The R^2 is the adjusted R-square in percent and is computed as the cross sectional average of individual adjusted R-squares. For better presentation and inclusion, the coefficients for $OINUM$ and $OIVAL$ are multiplied by 10^6 and 10^9 respectively. In the fourth row for each variable the standardized coefficient is reported.

Variable	Return Interval (Minutes)									
	One		Two		Three		Five		Ten	
Pre-Event Window										
Mid Point	-0.041	-0.039	- 0.032	- 0.030	-0.024	-0.023	- 0.021	-0.020	-0.014	-0.013
$Return_{t-1}$	(-3.72)	(-3.69)	(-3.35)	(-3.30)	(-2.30)	(-2.28)	(-1.20)	(-1.17)	(-0.23)	(-0.21)
	(-3.25)	(-3.21)	(-2.42)	(-2.39)	(-1.92)	(-1.85)	(-0.70)	(-0.68)	(-0.15)	(-0.14)
	-0.041	-0.039	- 0.032	- 0.030	-0.024	-0.023	- 0.021	-0.020	-0.014	-0.013
$OINUM_{t-1}$	0.92		0.83		0.76		0.70		0.25	
	(4.82)		(4.33)		(3.85)		(3.23)		(1.82)	
	(3.93)		(3.32)		(2.44)		(1.93)		(1.02)	
	0.28		0.23		0.18		0.07		0.05	
$OIVAL_{t-1}$		2.31		1.90		1.33		0.80		0.58
		(4.70)		(4.41)		(4.02)		(2.89)		(2.03)
		(3.98)		(3.15)		(2.43)		(1.92)		(1.18)
		0.24		0.19		0.13		0.05		0.03
R^2	1.13	1.12	1.04	1.02	0.73	0.71	0.46	0.44	0.20	0.21
Post-Event Window										
Mid Point	-0.045	-0.044	- 0.038	- 0.037	-0.029	-0.027	- 0.026	-0.023	-0.017	-0.016
$Return_{t-1}$	(-4.92)	(-4.88)	(-3.58)	(-3.55)	(-2.50)	(-2.45)	(-1.28)	(-1.25)	(-0.30)	(-0.27)
	(-3.49)	(-3.45)	(-2.62)	(-2.59)	(-2.02)	(-1.93)	(-0.76)	(-0.72)	(-0.18)	(-0.16)
	-0.045	-0.044	- 0.038	- 0.037	-0.029	-0.027	- 0.026	-0.023	-0.017	-0.016
$OINUM_{t-1}$	0.97		0.89		0.82		0.75		0.31	
	(4.99)		(4.47)		(4.12)		(3.46)		(1.99)	
	(4.13)		(3.47)		(2.63)		(2.33)		(1.19)	
	0.30		0.25		0.20		0.09		0.06	
$OIVAL_{t-1}$		2.45		2.11		1.46		0.92		0.66
		(4.91)		(4.60)		(4.18)		(3.11)		(2.32)
		(4.17)		(3.38)		(2.62)		(2.09)		(1.47)
		0.26		0.21		0.15		0.07		0.05
R^2	1.17	1.15	1.05	1.03	0.78	0.73	0.53	0.49	0.21	0.23

Concluding Remarks

In the first chapter, we provide the first ever evidence on the non-existence of the well documented [HKS \(2010\)](#) intraday momentum in the Chinese A-shares market. We also provide evidence on the existence of the intraday momentum pattern in two other international markets outside the United States which are China and Brazil. We then explore potential reasons to explain the non-existence of the pattern in Chinese markets. Instead of taking the route advocated by [Chui, Titman, and Wei \(2010\)](#) who explain the lack of momentum in longer term returns in East Asian market by using the level of individualism in these markets and attributing the weak level of momentum to the low levels of individualism in these countries we take the route advocated by [Chui and Titman \(2017a\)](#) as it uses a more unique feature of Chinese stock markets- the dual listed A-shares and B-shares which are owned by different types of investors, retail and institutional.

We find that the [HKS \(2010\)](#) intraday momentum pattern is far more prominent in dual listed B-shares as compared to their A-share counterparts. This indicates that institutional investors are primary drivers of the momentum pattern. To further test our findings, we use the inclusion of 232 A-shares in the MSCI index to study the impact of the inclusion of these shares on the proliferation of the intraday momentum pattern in the pre and the post event window. We find that the inclusion lead to a greater ownership and participation by institutional investors in the included stocks. Also, in the post event window these stocks exhibit a remarkably higher intensity of the intraday momentum pattern. This further proves the findings of previous studies like [Kaniel, Saar, and Titman \(2008\)](#) which claim that institutional investors are likely to be more persistent in their trading and generate the momentum effect. We also note that there is an intraday return reversal effect unique to Chinese markets which shows that retail investors bound by the day trading rule in China like to play out contrarian strategies which is in line with the findings of [Campbell, Ramadorai, and Schwartz \(2009\)](#) who claim that retail investors are mostly contrarian investors by nature.

We ensure that our findings are robust and are not driven by other phenomenon in

finance such as the bid-ask bounce which can potentially confound our results. This is done by taking a measure of return as advocated by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#) which mitigates any confounding inferences that we may have made due to the nature of our return measure. Our findings provide evidence that owing to the efforts of policy makers to improve key aspects of the stock markets in China that lead to the inclusion of A-shares in the MSCI index, we can see that the seeds for a greater role of institutional investors in Chinese markets have been sown and our results indicate that they have begun to bear fruit. As the scope of the MSCI inclusion increases and medium and small firms continue to get included in the index, future research could be done to further study the impact of MSCI inclusion on institutional holdings and ownership.

Recent studies such as [Alvarez, Jara, and Pombo \(2018\)](#) find that higher institutional ownership leads to increased corporate investment, lower sensitivity to cash flows and lower financial constraints for firms in emerging markets. Our findings indicate that there is a shift in the intraday momentum trading pattern that indicates the emergence of the power that institutional investors have in driving markets and the increasing level of institutionalization of Chinese markets. These findings are significant for both investors and policy makers alike. For investors, they show that the Chinese markets are beginning to mature and offer a potential entry opportunity. For policy makers, these findings show that their efforts and policies to transform the Chinese markets are paying off.

In the second chapter, I examine the intraday market efficiency of the entire population of the Chinese A-shares market. This is the first study that takes in to account the entire sample and for such a large period of time (three years). In addition to taking the entire population of stocks, I also ensure I employ two of the most widely used measures of intraday market efficiency as also employed by [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#). The two measures of market efficiency that we use are the intraday return predictability measure and the variance ratio tests.

The variance ratio test measure allows us to investigate the level of market efficiency during the 8 half-hour trading intervals in the Chinese stock exchanges. We find that the market efficiency is at the lowest level during the first half hour trading interval of the trading day and relatively lower than other half hour trading intervals in the half hour session immediately post the lunch break i.e. the 1:00-1:30 pm interval. These results can be reconciled based on the fact that the first half hour trading interval during the day is a particularly busy interval in terms of economic news arriving in the markets and

the absorption of over night information based on trading in the New York session as elaborated in the study by [Gao, Han, Li, and Zhou \(2018\)](#).

In addition to these features of the market efficiency of Chinese stocks, in Chapter Two, we also unravel the impact of limits of arbitrage such as the price limit rule, limited inclusion in CSI 300 and the MTSS program on market efficiency. We conclude that lower limits of arbitrage shorten the time it takes for removing intraday return predictability and the variance ratios are closer to unity for lower limits of arbitrage group stocks. This provides a strong motivation for future research on how to reduce limits of arbitrage in Chinese markets and thereby make the markets more efficient.

Furthermore, we also examine the impact of another land mark event facilitated by the Chinese market regulators- Shenzhen Stock Connect. For the first time in decades foreign investors registered in Hong Kong were allowed to trade on smaller stocks listed on the Shenzhen stock exchange. We employ an event study methodology to study the impact of this on market efficiency. Our results indicate that the Shenzhen Stock Connect program significantly improved market efficiency as indicated by both the measures of efficiency employed. This provides us with further evidence of the positive steps being taken by Chinese market regulators and the efficiency enhancing impact of these steps. These findings further provide critical empirical evidence on the nature of the efficiency of the Chinese markets. In particular, they highlight the impact of moves to lower the limits of arbitrage by enabling foreign investors to invest in mainland China shares by allocating higher permissible flows and trading volume.

Future research should be directed towards studying the impact of other pilot programs that the regulators may undertake to reduce limits of arbitrage. Also, these findings should provide impetus to investors to invest in Chinese stocks with greater confidence. They demonstrate that stocks with good analyst coverage, index inclusion in China Securities Index 300(CSI 300), coverage under the Marginal Trading and Short Selling programs (MTSS), which are also heavily traded and liquid at emerging stock exchanges like China, have market efficiency levels comparable to developed markets when compared to the findings of [Rösch, Subrahmanyam, and Van Dijk \(2016\)](#). Future research should be directed at determining what steps need to be taken to lower the limits of arbitrage and further enhance market efficiency.

The third chapter empirically examines the impact of three types of uncertainties economic policy, political and trade policy uncertainty on market liquidity. In a panel

regression and event study regression framework we study the impact of these three types of uncertainties on market liquidity. We use the [Baker, Bloom, and Davis \(2016\)](#) measure to gauge the economic policy uncertainty on a monthly basis. The trade policy uncertainty is gauged for the purposes of the panel regression by using the [Davis, Liu, and Sheng \(2019\)](#) monthly index measure. For the liquidity measures, we use proxies for the transaction costs and price impact.

On a broad level, our findings indicate that all three uncertainties economic policy, political and trade policy uncertainty have an adverse impact on liquidity. We further explore the differential impact of these uncertainties on various sectors of the stock market. We find that the liquidity of the most policy sensitive industries comprising Financials and Real Estate exhibit the highest level of adverse sensitivity to economic policy uncertainty. In contrast, they exhibit the least sensitivity to trade policy uncertainty. The manufacturing sector exhibits the most sensitivity to the trade policy uncertainty measure. The measure has been particularly elevated since the recent break out of the trade war between China and the United States.

Furthermore, we employ the event study regression methodology to study the impact of the Bo political scandal on SOE versus non SOE enterprises and note that the adverse impact on the liquidity of SOE enterprises owing to political uncertainty arising from the scandal was lower as compared to the adverse impact on non SOE firms. This shows that non SOEs are more prone to liquidity problems associated with fire sales during political crises. This should prepare investors and policy makers to better anticipate the impact of political crises of stocks they own and depending on their desired level of risk they might chose to take appropriate action with regard to their position.

Finally, we use the break out of the trade war between the US and China and study its impact on the market efficiency of the Chinese stock market. Our findings indicate a significant deterioration in the levels of market efficiency as indicated by both our intraday market efficiency measures- the intraday predictability measure and the variance ratio tests. This contributes to the existing body of literature regarding the harmful impact of trade wars on markets and economies. It is a timely finding and provides useful insights in to the perils of a trade war for financial markets.

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