

University of Nottingham
UK | CHINA | MALAYSIA

Essays on Input Trade Liberalization, Productivity and Exporting

Thesis submitted to the University of Nottingham for the degree of **Doctor of Philosophy, December 2022.**

DONG Wenxiao

School of Economics
University of Nottingham

Supervised by

Dr. Zhihong Yu
Dr. Yuan Tian

Signature _____

Date _____ / _____ / _____

Abstract

This dissertation comprises three essays on input trade liberalization, productivity and exporting. The first chapter studies the impact of input trade liberalization on economics with sizeable input and output distortions. The last two essays investigate imported industrial robots and their economic impact. In chapter 2, I build a Melitz model incorporating firm-level output, domestic input, and foreign input distortions to show that the input trade liberalization can improve resource allocation, and leads to an increase in the aggregate TFP. A quantitative exercise indicates that the input trade liberalization increases the aggregate TFP under sizeable distortions. Moreover, We find that the selection effect induced by the input trade liberalization under distorted cases is stronger than that under the distortion-free case. In Chapter 3, I use Chinese manufacturing data and custom data to construct a dataset to show the firm-level robot adoption among Chinese manufacturing firms. I employ this dataset to analyze the effect of robot adoption on exporting, especially on exporting extensive margin and intensive margin, using the PSM-DID empirical method. I find that the rise of imported robot adoption significantly increases export sales and the extensive margin, through increasing efficiency. In terms of the intensive margin, robot adoption has no significant effect in general. In Chapter 4, I turn attention to the effect of robot adoption on firms' innovation activities. I construct another dataset with Chinese manufac-

turing data, customs data and patent data. I find that the use of robots imported from developed countries significantly increases firms' innovation, especially in patent filings, through increased productivity and hiring more high-skill labour.

Acknowledgements

This dissertation wouldn't have been possible without the exceptional guidance and unwavering technical support I received from my Supervisors: Dr. Zhihong Yu, Dr. Yuan Tian, and Dr. Alejandro Riano. In particular, I am profoundly grateful to Dr. Zhihong for his continuous encouragement and patience throughout my Ph.D. studies and research. He generously provided me with all the support I could have hoped for. I also extend my gratitude to Dr. Yuan Tian for her valuable advice and feedback during the final year of my PhD program. Additionally, I would like to thank Dr. Alejandro Riano for his unwavering support, which played a pivotal role in developing the framework for the first chapter of this thesis.

I express sincere appreciation to the other esteemed faculty members and colleagues of the School of Economics. I am grateful to Prof. Facundo Albornoz, Dr. Roberto Bonfatti, Prof. Gianni De Fraja, Prof. Markus Eberhardt, Prof. Giovanni Facchini, Prof. Giammario Impullitti, Prof. Omar Licandro, Prof. Daniel Seidmann, and Prof. Richard Upward for their exceptional training and advice during the PhD presentation meetings. I would also like to thank Natalia Bas for her efficient administrative support.

Throughout the years, I have greatly benefited from discussions, both formal and casual, with numerous knowledgeable and supportive friends. It is impractical to list them all individually. I want to acknowledge the assistance of Dr. Guo Longfei, Dr. Thomas Chen, Dr. Jiang Haicheng, Dr. Xiang Pengfei, Dr. Zhang YUzhu, Dr. Hayat Ahmadzai, Dr. Juan C. Rosas, Dr. Miriam Saldana, Dr. Antonio Carrillo, Dr. David, Dr. Chaoqun Zhan, Dr. Hu Xinyue, Mr. Chen Jipeng, and Mr. Liu Zhenxing.

Finally, I cannot conclude this journey without recognizing the unconditional love and support of my father Dong Yongzhou, my mother Chen Xiling, my mother-in-law He xilian, my wife Feng Huafen, my two-year-old

daughter Dong Shuyu, and my younger brother Dong Wenkang. I can only express my heartfelt gratitude and look forward to spending more quality time together with you.

Contents

Abstract i

Acknowledgements iii

List of Tables viii

List of Figures ix

Abbreviations 1

Chapter 1 Introduction 1

1.1 Thesis overview 5

1.2 Thesis outline 8

Chapter 2 Input Trade, Misallocation and Productivity 9

2.1 Introduction 9

2.2 Literature review 14

2.3 Background of China's misallocation 22

2.4 Theoretical framework 24

2.5 The data 38

2.6 Quantitative analysis 41

2.7 Conclusion 53

Chapter 3 Imported Robots and Exporting Performance 54

3.1 Introduction 54

3.2 Literature review 59

3.3 The Data 67

3.4 The empirical methodology 76

3.5 Results 83

3.6 Robustness tests 89

3.7 Further analysis 93
3.8 Conclusion 103
Chapter 4 Imported Robots and Innovation 105
4.1 Introduction 105
4.2 Literature review 109
4.3 Institutional background of IPR regulation and the patent system in China 114
4.4 The data 118
4.5 The empirical methodology 124
4.6 Results 131
4.7 Robustness tests 133
4.8 Further analysis 136
4.9 Conclusion 143
Chapter 5 Conclusions 144
Bibliography 146
Appendices 165
Appendix A Theoretical framework 166
A.1 Closed economy heterogeneous firm model 166
A.2 Two-country open economy model 172

List of Tables

2.1 Summary statistics: firm performance (year 2005) 40
2.2 Calibration model with heterogeneous distortions 44
2.3 Counterfactual analysis 50
2.4 Counterfactuals analysis with specific distortions 51

3.1 Summary statistics 71
3.2 Firm characteristics (Mean and Std.Dev) by robot adopter status 74
3.3 Definition of main variables 75
3.4 Robot effect on export (OLS) 78
3.5 Robot effect on export (DID) 84
3.6 Balancing tests 87
3.7 Matched firms 87
3.8 Robot effect on export (PSM-DID) 88
3.9 The alternative definition of new robot adopter (001) 91
3.10 The alternative definition of new robot adopter (0001) . . . 91
3.11 Alternative time periods (2000-2009) 92
3.12 Robot effect on export (dynamic effect) 95
3.13 Channel test 97
3.14 Capital-labour ratio 100
3.15 Ownership 101
3.16 Total factor productivity 102

4.1 Summary Stastics 121

4.2 Firm Characteristics (Mean and Std.Dev) by ownership, location and industry 122
4.3 Definition of main variables 123
4.4 Robot effect on innovation (OLS) 126
4.5 Variable balancing test 130
4.6 Matched firms 130
4.7 Robot effect on innovation (PSM-DID) 132
4.8 Firm-level productivity 134
4.9 Firm location 135
4.10 Channel test 138
4.11 Capital-labour ratio 139
4.12 Firm size 141
4.13 Ownership 142

List of Figures

1.1 China's import value 4

2.1 Import intensity among importers 40
2.2 Shares of four types of firms (open economy distorted case) 45
2.3 Gain from input trade liberalization 50
2.4 Gains from trade with different distortions 52

3.1 China's robot stocks from 2000 to 2013 69
3.2 Industrial Composition of Robot installation in China . . . 70
3.3 The parallel trend 95

4.1 China's patent filing from 2000 to 2013 121
4.2 The parallel trend 137

Chapter 1

Introduction

China's unparalleled economic growth in the past four decades has earned it the reputation of being "the world's factory". This remarkable economic development has been achieved despite challenges such as economic transition, privatization and state-owned enterprise (SOE) Reforms, widespread corruption, and inadequate intellectual property protection (Song et al. (2011); Bai et al. (2020a); Bai et al. (2020b); Hsieh and Song (2015)). Understanding the driving forces behind this great improvement is important. The country's access to the global market and integration of new technologies has been crucial factors in its economic success (Khandelwal et al. (2013); Brandt et al. (2017); Storesletten and Zilibotti (2014)). These two factors enhance resource redistribution across various sectors and within particular firms. Brandt et al. (2012) acknowledges that up to two-thirds of the overall increase in total factor productivity (TFP) within manufacturing results from the selection effect: entry of highly productive firms and exit of low-productivity ones from the domestic or international market. The classical growth theory always emphasizes the delay in imitating and adopting new technology in developing nations, resulting in a produc-

tivity gap between the Global North and Global South countries (Acemoglu et al. (2006)).

China exhibits certain distinctions. For the last 40 years, China's manufacturing sector has made significant advancements, with continuous improvements in trade liberalization, automation and innovation capabilities. Since 2009, China has held the position of the world's largest exporter and the second-largest importer. Though China embraced a process of export-led growth after economic reform, China's import value, as shown in Figure 1.1, also has grown from 0.23 trillion USD to 2.69 trillion USD. Five years ago, during the China International Import Expo's Opening Ceremony, the Chinese government expressed its commitment to expanding China's market opportunities globally by opening up its economy. The adoption of technology in use in developed countries is likely to be a potential engine of growth in China, given China's average enterprise and labour productivity lags behind that of developed countries.

Another significant characteristic of China's economy is its widespread adoption of automation (Belton et al. (2020)), which exemplifies how swiftly China embraces advanced technology. Despite being a developing country, China has emerged as a leader in global robot adoption, distinguishing itself from other developing nations (Chen et al. (2017); Cheng et al. (2019)). Despite having abundant labour resources and lower labour costs compared to developed countries, the Chinese government has actively supported the robotics industry and manufacturing automation through industrial policies and subsidies, even if it may lead to labour displacement (Yang (2017)). Most of the robots and automation equipment used in China are imported from developed countries, facilitated by the liberalization of intermediate goods trade, as analyzed by the International Federation of Robotics (IFR). The improvements in China's manufacturing level have resulted in a surge

in manufacturing exports, making China the largest trading partner for many countries worldwide. Though foreign direct investment has been a major driver of technology transfer, domestic investment in innovation also plays an important role. Furthermore, China's economic development is closely tied to its continuous enhancement of innovation capacity, far ahead of any other country at a comparable development stage. Although China lags behind developed countries in terms of intellectual property protection and patent law enforcement, it has made significant strides in innovation and has become the world's largest patent applicant in recent years. Although the imitation-based approach has drawn criticism regarding potential intellectual property issues, it has facilitated learning and subsequent innovation, fueling the growth in China's industries, like the automotive and ICT sectors. China is the world's largest producer and consumer of automobiles and the largest producer of ICT products. The development of these industries began with imitation, leading to concerns about potential infringement of intellectual property rights. To access the Chinese market, European, Japanese, and American automakers such as Volkswagen, Toyota, and General Motors had to collaborate with China's state-owned enterprises, allowing Chinese manufacturers to progress from learning to production and eventually innovation, contributing to their growth and expansion. Currently, the automotive industry in China has achieved high levels of automation. Similarly, in the ICT industry, particularly the smartphone sector, companies like Apple have shifted their production and processing chains to China, capitalizing on its cost-effective labour force and fully automated production workshops, which has benefited local Chinese companies through learning and utilization. The spillover of knowledge has played a crucial role in driving advancements in these two industries. Overall, China's accession to the WTO, trade liberalization, and manufacturing automation have all had a profound impact on fostering innovation

in its enterprises.

China's remarkable economic development can be attributed to its adoption of trade liberalization and integration of new technologies. In this thesis, we conduct three studies to estimate the effects of input trade liberalization on Chinese firms' productivity, exports, and innovation activities.

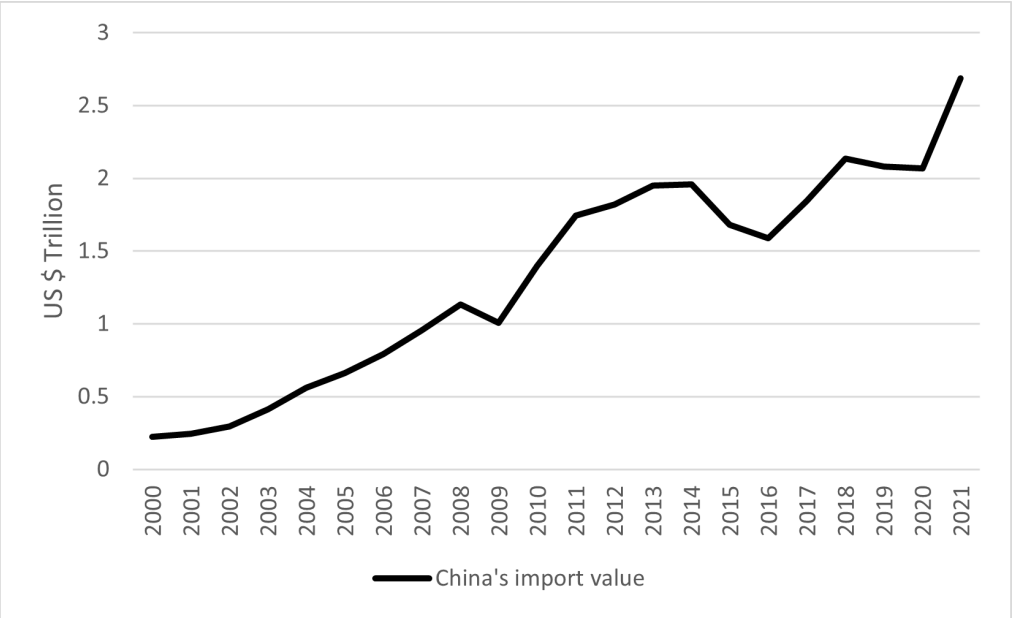


Figure 1.1: China's import value

1.1 Thesis overview

This section provides an overview of the whole thesis by summarising the questions, main results and contribution of the three chapters.

Chapter 2 answers the question that what is the impact of input trade liberalization on aggregate TFP with sizeable output, domestic and foreign input distortions. In particular, what is the role of intermediate input distortions? Some recent literature explores the effect of imported inputs - which constitute the majority of world trade – on firm productivity. They find that trade liberalization on the foreign intermediate input has significantly increased firms' productivity in several countries (for example, Yu (2015); Liu and Qiu (2016); Amiti and Konings (2007); and Topalova and Khandelwal (2011)). Hsieh and Klenow (2009), Song et al. (2011) and Bai et al. (2019) show that the misallocation of resources in the manufacturing sector across heterogeneous firms is sizable and ubiquitous, causing a reduction in aggregate TFP in China.

I build a quantitative two-country heterogeneous firms trade model with firm-specific distortions, which combines Melitz (2003) and Hsieh and Klenow (2009), and also includes the use of imported intermediate input. There are four dimensions of heterogeneity at the firm level: productivity, output and domestic and foreign input distortions. With the comprehensive data of Chinese manufacturing firms, I quantify the trade liberalization effects.

With the calibrated parameters, I find that input trade liberalization increases the aggregate TFP even under sizeable distortions (Amiti and Konings (2007); Yu (2015); Brandt et al. (2017)); the three distortions reduce aggregate TFP by 47.9% compared to the distortion-free scenario, which

is a similar magnitude to the findings of Hsieh and Klenow (2009). More precisely, the total factor productivity (TFP) of the case with only domestic input distortion is 23.6% lower than the distortion-free case, confirming previous findings of significant domestic resource misallocation in Chinese research. (Bai et al. (2019); Song et al. (2011);Song and Wu (2015);Chen et al. (2019)). Moreover, the elasticity of aggregate TFP with respect to the reduction of the input iceberg trade cost is positive and larger under distorted cases than that in the distortion-free case. This result is consistent with Bai et al. (2019)'s finding that the selection effect of the trade liberalization under the distorted case is stronger than that under the distortion-free case. As far as I know, this is the first paper to study the impact of input trade liberalization on economics with sizeable output, domestic and foreign input distortions.

Chapter 3 aims to address the question of how the adoption of imported robots, embedded with high technology from developed countries, will impact the exporters' extensive and intensive margins. The literature reveals that Most works focus on how automation affects employment, wage and reshoring in developed countries. Few paper study the impact of robot adoption on firms' exports, especially from the perspective of a developing country.

We merge the customs data collected by the Chinese General Administration of Customs (CGAS) with the Chinese manufacturing firms' data from the *Annual Survey of Industrial Firms* collected by the Chinese National Bureau of Statistics(NBS) and use the sample period from the year 2000 to 2013. We apply a combination of propensity score matching (PSM) and difference-in-difference (DID) techniques to conduct the causal relationship between robot adoption and the extensive and intensive margins.

The main results indicate that using robots will significantly increase firms' export sales and extensive margins. However, the impact on the intensive margins follows a different trend. The estimates indicate that, on average, robot adopters exhibit an 8.6% increase in the number of product-country pairs, a 14.6% increase in the number of exporting products, and a 3.9% increase in the number of exporting countries. There is no significant alteration in the average exporting value per pair and per country. The average exporting value per product experiences an 8% decline among robot adopters. From the results, we can see that the adoption of robots significantly increases the total exports of firms, which echoes some research (Acemoglu and Restrepo (2018); Artuc et al. (2019); Bernard et al. (2010); Alguacil Marí et al. (2020)). Regarding the extensive margins, Alguacil Marí et al. (2020) finds that robot adoption increases firms' export probability; Bernard et al. (2010) discover that the heightened efficiency will enhance the range of products offered by the companies and enable them to set higher prices in both the local and global markets. Then we turn to the intensive margins, after the application of robots, multi-product firms, driven by the objective of enhancing productivity and maximizing profits, inevitably make adjustments to their export product range. They will reallocate the enterprise's factor resources among different types of products. Bernard et al. (2010) also discover that the emergence of new products will squeeze the market share of existing products and reduce their profitability. In my study, the adoption of robots greatly boosts total export value and diversity, with no significant impact on intensive margins. We test the impacting channel of robots adoption in export, TFP plays a role in the mechanism.

Chapter 4 aims to address the question of how the adoption of imported robots, embedded with high technology from developed countries, will im-

pact firms' innovation activities. In this research, the innovation activities of firms are measured by patent filings. We combine the NBS dataset, customs dataset and patent dataset from the China National Intellectual Property Administration (CNIPA). In this research, we combine propensity score matching (PSM) with the difference-in-difference (DID) method to estimate the causal relationship between robot adoption and innovation activities.

The main results indicate that robot adoption will significantly increase firms' innovation activities (total patent and invention patent). The high capital-labour ratio tends to experience greater increases in innovation intensity, as do private firms. The major contribution of this chapter is enhancing the understanding of robots and innovation activities and enriching the imports and innovation literature.

1.2 Thesis outline

The rest of this thesis proceeds as follows. Chapter 2 examines the impact of input trade liberalization on economics with sizeable output and domestic and foreign input distortions. Chapter 3 investigates the effect of imported robot adoption on the extensive and intensive margins of exports. Chapter 4 estimates the effect of imported robot adoption on innovation activities. Chapter 5 is the conclusion.

Chapter 2

Input Trade, Misallocation and Productivity

2.1 Introduction

China experienced unprecedented productivity growth in the manufacturing sector over the last four decades. Deeper integration with the world economy is exemplified by substantial growth in exporting and importing (e.g. Brandt et al. (2017); Yu (2015)). International trade theory provides a clear rationale for the beneficial effects of trade liberalization on aggregate productivity growth - trade liberalization enables more efficient production across countries, sectors and firms which leads to aggregate productivity growth Melitz (2003); Topalova and Khandelwal (2011); Melitz and Trefler (2012). Some recent literature explores the effect of imported inputs – which constitute the majority of world trade – on firm productivity. They find that trade liberalization on the foreign intermediate input has significantly increased firms' productivity in several countries (see Yu (2015), Liu

and Qiu (2016), Amiti and Konings (2007), and Topalova and Khandelwal (2011)).

China faced prevalent policy and institutional distortions, which can potentially distort the efficient allocation of resources across firms and have a sizeable negative effect on economic outcomes (Hsieh and Klenow (2009); Song et al. (2011); Hsieh and Song (2015); Bai et al. (2020a)). Generally, there are several potential sources of misallocation. There are provisions of tax that vary with heterogeneous firms' characteristics (e.g. size-dependent tax in India). Misallocation may be created by the crony behaviours of the government or other entities (such as banks) that favour specific firms. For example, there are low-interest rate loans for firms with a special relationship, specific trade and industry policy for narrow sectors, preferential market access for state-owned firms, and selective enforcement of taxes and regulation - which distort the allocation of resources away from their most efficient use(Ahn et al. (2011); Song and Wu (2015); Bai et al. (2018)). Hsieh and Klenow (2009) —henceforth, HK —and Song et al. (2011) show that the misallocation of resources in the manufacturing sector across heterogeneous firms is sizable and ubiquitous, causing a reduction in aggregate TFP in China. HK's new perspective shows that in an economy with heterogeneous production units, aggregate TFP depends not only on the TFP of the individual production units but also on how inputs are allocated across these production units. HK use micro-data on plants in the manufacturing sector in China, India and the US to measure the size of establishment-specific tax rates. They measure sizable gaps in marginal products of labour and capital across plants within narrowly defined industries in China compared with the US. In addition, when capital and labour are hypothetically reallocated to match marginal products to the extent observed in the US, they calculate manufacturing TFP gains of 30%

- 50% in China. Khandelwal et al. (2013) shows that inefficient allocation of the externally imposed export quotas significantly reduces the aggregate productivity.

A question of interest is how trade liberalization in intermediate inputs affects the aggregate TFP and welfare in the presence of firm heterogeneity and resource misallocation. In particular, what is the role of intermediate input distortions? This question lies at the intersection of trade and the misallocation literature. I build a quantitative two-country heterogeneous firms trade model with firm-specific distortions, which combines Melitz (2003) and Hsieh and Klenow (2009), and also includes the use of imported intermediate input. With the comprehensive data of Chinese manufacturing firms, I quantify the trade liberalization effects.

Following China's WTO entry, tariff reductions led to strong import growth. From 2000 to 2006, the total value of China's intermediate imports increased by 256% (Brandt et al. (2017)). They also find that for the manufacturing sector, the fraction of firms using imported intermediate inputs was 7.1% in 2007, and the share of imported intermediate in total inputs used for the entire manufacturing sector was 7.5% in 2007 in ordinary trade in China. Moreover, at the microeconomic level, not all firms take the same advantage of accessing these cheaper or higher quality imported intermediate inputs in the presence of certain distortions. So intermediate inputs market frictions could generate an additional misallocation across heterogeneous firms and aggregate TFP loss.

In this paper I assume firms use two kinds of factors: labour and intermediate inputs. There are four dimensions of heterogeneity at the firm level: productivity, output and domestic and foreign input distortions. Like in HK's paper, domestic and foreign input distortions are assumed

to be intermediate input wedges, and they drive differences in the marginal products of inputs across firms. The correlation between productivity and distortions is taken as exogenous in Ho (2010) and Costa-Scottini (2018)), they assume a size-dependent distortion based on the observed empirical evidence or specific government regulation. Different from their assumption, I assume productivity and input distortions follow different distributions and are independent of each other. Because the observed empirical facts (i.e. positive or negative correlation) are not the true relationship. This assumption is consistent with the evidence in Bai et al. (2018). They find that the observed positive correlation is determined by a combination of a selection mechanism and the underlying correlation. In the presence of misallocation, firms that benefit from international trade and lower marginal cost need not necessarily be the high-productive ones, so it is no longer clear whether the trade-induced reallocation contributes to welfare gains.

I introduce international trade components into HK's framework, namely, the imported intermediate inputs. Berthou et al. (2018), Bai et al. (2018), Costa-Scottini (2018) and Chung (2018) focus on the firms' export behaviour. Gopinath and Neiman (2014) analyze the sourcing strategy, fixed import cost and roundabout production, without final goods exporting or distortions. My work is broadly complementary, as I investigate the effect of trade liberalization on both importing and exporting behaviours. In the presence of resource misallocation, relatively subsided firms will expand more, rather than the true more productive firms. On the extensive margin, firms that use imported intermediate input and exporting may just receive high subsidies at the cost of more productive firms. Distortions will affect the trade effects on aggregate productivity, selection channel(exit and importing), and misallocation. So I can use this model to quantitatively examine the impact of trade liberalization on imported intermediate inputs

in a heterogeneous firms trade model with potential inputs distortions.

Lastly, I use this estimated model to quantify the impact of input trade liberalization on aggregate TFP and welfare with several counterfactual experiments. With the calibrated parameters, I find that the three distortions decrease the aggregate TFP by 47.9% compared to the distortion-free case. More specifically, the aggregate TFP of the distorted case with domestic input distortion only is 23.6% less than the distortion-free case. Another main finding in the analysis is that the aggregate TFP increased by 3.11% under a distorted case, as well as a 1.1% increase in aggregate TFP under a distortion-free case when the input iceberg trade costs decreased by 20%. That is to say, the elasticity of aggregate TFP with respect to the reduction of the input iceberg trade cost is positive and larger under distorted cases than in the distortion-free case. Khandelwal et al. (2013) show that if trade barriers are managed by inefficient institutions, trade liberalization can lead to greater-than-expected gains.

The organization of the paper is as follows. Section 2 is the literature review and the background of China's misallocation. Section 3 derives a theoretical framework of a two-country endowment trade model in the presence of distortions. Section 4 is the description of the dataset. Section 5 numerically examines the impact of trade liberalization on aggregate TFP. The last section concludes.

2.2 Literature review

2.2.1 Theory of misallocation

This paper contributes to several strands of literature. In the traditional development literature, a consensus is that the differences in productivity account for much of the variations in living standards between developing and developed countries. Generally, developing countries are slow to adopt new technologies, even though they have a similar quantity and quality of factors used in production such as capital, labour, and other intermediate inputs (Syverson (2011)). Key papers by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) focus on the misallocation of resources across firms, rather than the productivity of a representative firm, which can have potential effects on the aggregate total factor productivity. Restuccia and Rogerson (2017)'s review study shows the causes and costs of misallocation.

Following Restuccia and Rogerson (2008) and Hsieh and Klenow (2009)'s analysis, we are specifically focusing on the distortions that only affect the allocation of input of the production across firms of a given firm-level productivity and inputs. They introduce that any factors that create misallocation can be thought of as generating wedges in the first-order conditions of the establishment optimization problem. The basic idea is to estimate the extent to which marginal revenue products (marginal revenue of capital, labour, intermediate input) are not equated across establishments, thereby generating estimates of the firm-specific tax rates. That is to say, given the amount of all inputs, different tax rates on heterogeneous producers will be misallocated across all the firms in a narrow industry. In addition, they only study establishments with positive production, their estimates do not reflect any selection effects in entry and exit.

More specifically, in Hsieh and Klenow (2009)'s model, each firm produces different varieties with a constant elasticity of substitution (CES) demand function. Each producer like the definition in Melitz (2003) behaves as a monopolistic competitor in the final goods market, but markets for the factors (capital and labour) are completely competitive. They assume that a firm's output price is a fixed markup over its marginal cost. Moreover, the revenue based on TFP does not vary across firms within an industry unless firms face specific distortions. They use microdata on plants in four-digit manufacturing sectors from the US, China, and India, and find large factors of misallocation in China and India compared to the supposed more efficient resource allocation in the US. Many prominent institutional and policy features of China and India intuitively generate that large misallocation. Haltiwanger et al. (2018) and De Loecker and Syverson (2021) challenge the measurement of misallocation in HK. They demonstrate that the homogeneous revenue-based TFP implication arises duo to the HK model, a producer's price has an elasticity of -1 with respect to its TFP level. However this crucial negative unit elasticity only occurs under the demand and supply conditions: each producer must face inelastic demand, and price can not fully respond to TFP differences. Among the empirical evidence of the measurement of misallocation, Bartelsman et al. (2013) apply variation in the within-industry covariance between size and productivity. In the case of China, Ding et al. (2016) apply the interquartile range and standard deviations of TFP, which reflects movements away from an optimal feasible resources allocation (Asker et al. (2014)). Bai et al. (2019) apply the dispersion of the revenue base TFP as the empirical measure of misallocation, following HK's method.

2.2.2 Sources of misallocation

I then move on to review the potential underlying sources of the misallocation. The statutory provisions including tax codes and regulations may generate misallocation in developing countries. Hopenhayn and Rogerson (1993) find that a tax on job destruction at the firm has a sizable negative impact on total employment and decreases average productivity. A broader category of policies of 'size-dependent regulations' reflects distortions that higher implicitly taxes on firms that are larger in terms of employment. India's government has some restrictions on large firms in the manufacturing sectors. For example, in Ho (2010)'s work, she studies the effect of trade liberalization on welfare with the regulation that a policy was reserving small-scale firms which exclusively produce specific manufacturing products. The quantitative analysis shows that the size-dependent distortions significantly reduce India's gain from trade by 40 per cent. Similarly, Costa-Scottini (2018) apply the size-dependent distortions on domestic firms in the open economy to rationalize the facts that developing countries are featured by small-scale local firms, high dispersion of individual productivity, and disproportionately low trade-to-output ratio. This research constructs a general equilibrium trade model and finds that distortions on the large firms will reduce their trade volume, gains from trade, and the aggregate TFP overall. Furthermore, the heterogeneous size-dependent distortions across countries may explain a substantial share of international productivity differences. Rather than studies in developing countries, García-Santana et al. (2016) show the effect of size-contingent laws using firm-level data between 1995 and 2007 from France where firms with 50 or more employees face potential additional discriminate regulations. Small-scale firms become the winner under the regulation. However, total welfare decreased by 3.4 per cent, equivalent to a 2.3 per cent variable

tax on labour.

Capital market friction may be one of the single most researched causes of resource misallocation. Many studies quantified the misallocation of capital across firms due to credit constraints. Specifically, Manova (2012) develops a heterogeneous firm model with countries at different levels of financial development and sectors with varying financial vulnerability. They find that a more efficient financial market may boost the economy in terms of a wider range of exporting products, fewer product turnover, and larger exporting destinations. Wu (2018) show that financial frictions are estimated to cause a reduction of 8.3 per cent of the aggregate TFP, which accounts for around 30 per cent of the capital misallocation in China. They also show a stylized fact on the Chinese economy that the average and dispersion of the marginal revenue of capital record significant differences across firms with different ownership (e.g. state-owner firms and private firms), which is also discussed in some literature (Hsieh and Klenow (2009), Song et al. (2011), Brandt et al. (2013)). In other words, the ownership structure is often taken as one of the policy distortions that lead to capital misallocation. Buera et al. (2011) show that financial frictions account for a substantial part of the differences in the cross-country aggregate and the sectoral level TFP. Furthermore, financial frictions have relatively fewer effects on non-tradable sectors than tradable and investment goods sectors, which have larger establishments with more financing needs. In terms of the developed countries (like Spain, Italy, and Portugal), Gopinath et al. (2017) develop a model with size-dependent financial frictions to illustrate that the decline in the real interest rate leads to a significant reduction in sectoral total factor productivity because capital inflows are allocated to firms with higher net worth but not necessarily higher productive, using data between 1999 to 2012. Midrigan and Xu (2014) find that financing

friction is quite large, both in Korea and Colombia. But the TFP loss from misallocation is quite small, which contradicts the finding of HK.

This paper is more related and complementary to intermediate goods misallocation literature. Jones (2011)'s paper tries to explain the larger differences in per capita income between the rich and poor countries through the channel of the efficient level of intermediate goods allocation. Specifically, besides labour and capital, intermediate goods' share of output is around 50 per cent, which is an amplification force echoing the familiar multiplier associated with capital accumulation. Wang (2017) incorporates a novel role of intermediate input frictions (e.g. pre-order and borrowing constraints on intermediate input), and tries to quantify the misallocation by the potential gross output gains, applying a similar method used by Hsieh and Klenow (2009) that hypothetically reallocate factors to equalize the marginal revenue of products across firms in a narrow industry. Finally, this paper finds that intermediate input frictions lead to half of the misallocation. Beŋkovskis (2015) finds a similar negative effect of intermediate input misallocation on the aggregate TFP in Latvia. With France's firm-level data, Sandoz (2017) analyzed the effect of increasing sourcing intermediate goods from China on the aggregate TFP after China's trade liberalization. More of France's highly productive firms pay the entry cost and outsource inputs at a lower price to reduce the marginal cost in the presence of distortions on local firms. This study decomposes the sectoral TFP growth into technical efficiency and allocative efficiency and finds that the gains of aggregate TFP are fully explained by higher allocative efficiency of market shares across firms. The potential impact of intermediate goods frictions on misallocation has not been fully investigated. Given that intermediate goods account for 70 per cent of gross output revenues, intermediate goods friction could potentially generate a large dispersion in marginal products

of intermediate goods, and thus cause measured misallocation in China.

2.2.3 Trade and misallocation

This paper is most closely related to concurrent studies on the role of firm-level distortions in a trade context. In the open economy, much literature quantifies the gains from trade. Amiti and Konings (2007) use Indonesia data and find that lower tariffs on intermediate inputs can increase plant productivity through learning, more varieties, and higher input quality. Another channel studied by Vandenbussche and Viegelahn (2016) shows that trade production on imported inputs may result in within-firm reallocation. Because of anti-dumping, Indian firms significantly reduce their use of protected imported input. This response to the import protection results in potential output loss, compared to other outputs without using protected imported intermediate inputs. Ramanarayanan (2020) and Blaum et al. (2017) show that firm-level heterogeneous input sourcing decisions affect the gains from trade. In an open economy with domestic distortions, trade may have an ambiguous effect on total welfare. With Chinese Data, Bai et al. (2019) employ a Melitz model incorporating firm-level wedge (like in Hsieh and Klenow (2009)) showing that trade liberalization can decrease rather than improve the allocative efficiency, resulting in a reduction rather than an increase in aggregate TFP. For the case of China with sizeable distortions, trade liberalization may not follow the highlighted mechanism of the new new trade theory that trade induces a resource reallocation from low-productive firms to high-productive firms. For example, in the presence of distortions in China, a firm can operate or enter the foreign market may not because of the inherently high productivity, but the sufficient subsidies. That is to say, a mass of highly subsidized but not adequately

productive firms will have more market share than they should have, at the cost of other real highly productive firms. In their model, they assume the wedges only distorted the individual-level productivity and have an impact on the export market, resulting in misallocation effects and selection effects. Berthou et al. (2018) construct complementary research that examines the gains from trade in the presence of firm-level heterogeneity and resource misallocation. They find several results: first, both export and import expansion increase aggregate welfare, and the former reallocates market share to more productive firms, while the latter acts in a contrast mechanism; second, more efficient institutions, factors, and final products markets improve the gains from import competition but engender welfare loss from export access.

I add literature on the implications of resource misallocation for aggregate growth and productivity and also contribute to vibrant research on the impact of institutional and market frictions on international trade.

2.2.4 Trade liberalization theory and empirical evidence

Krugman (1979) and Helpman and Krugman (1987) built theoretical international trade models that incorporate final goods, and discovered productivity gains arise due to scale effects. In their models, with the reduction of the tariff on the final goods, exposure to the foreign firms' competition increases the elasticity of demand faced by domestic producers, reducing market power and forcing firms down their average cost curves. Gains could also arise due to the reallocation effect, with more efficient plants gaining market share, driving the least efficient plants out of the market, and hence increasing the average industrial productivity. (Melitz (2003)). Other po-

tential gains from the trade liberalization can be scientific and technological knowledge flows from abroad due to international trade (Grossman and Helpman (1991)), or domestic knowledge spillover and learning by doing (Amiti and Konings (2007); Krugman (1987)). Some researchers focus on the theoretical models analysing the effect of reducing input tariffs and find that lower input tariffs can lead to increased productivity due to access to more varieties of intermediate input, access to higher quality imported inputs and through learn effects (Grossman and Helpman (1991); Markusen (1989)). Among the empirical evidence of the trade liberalization, Amiti and Konings (2007) confirm that lower output tariffs can increase productivity by inducing tougher import competition and that gains from reduction of input tariffs is at least twice as much as from cutting output tariffs using Indonesian firm-level data. Topalova and Khandelwal (2011) examine the effect of India's trade reform in the early 1990s, and find that reduction in trade protectionism led to higher levels and growth of firm productivity, with the effect strongest for private firms. Turning to the application to China, Yu (2015), with Chinese manufacturing firms data, find that a reduction in input trade cost for large firms leads to an increase in export intensity and the probability of firms' being new exporters. This positive effect is more pronounced for ordinary trade firms than hybrid firms which engage in both ordinary trade and processing trade. Fan et al. (2019) examine how final goods producers' exit, entry, output and exporting decisions respond to trade liberalization in imported intermediate inputs, and how this response differs across sectors.

2.3 Background of China's misallocation

The prevalence of distortions exists in the Chinese economy, and they are sizable and take different forms, including taxes and government subsidies, implicit guarantees issued by the authorities, preferential access to capital and land through informal special deals, industrial policy, and export promotion in the special economic zones. After over 40 years of economic reform, the most reliable explanation for the unexpected economic growth in China is the gradual improvement of formal economic institutions (Song et al. (2011)).

The dramatic transformation of state-owned firms plays an important role in economic expansion. Specifically, the small and low labour and capital-productive state-owned firms were closed, and the large state-owned firms were corporatized and merged into large industrial groups under the control of the state. Hsieh and Song (2015) Use firm-level Chinese data from 1998 to 2007 and show that: the labour productivity of both state-owned firms increases to a similar level as that of private firms; the capital productivity of state-owned firms remains significantly lower than that of private firms; the TFP growth is faster in state-owned firms; the reform of state-owned firms - grasping the large, letting go of the small - accounts for around 20 per cent of aggregate welfare growth in the sample period of China.

Bai et al. (2020a) document the widespread use of special deals in China with poor formal institutions, like no clear formal legal protection for private property, no independent judiciary that enforce contracts and adjudicates commercial dispute (Xu (2011); Robinson and Acemoglu (2012); Bai et al. (2020b)). China had substantial policy-induced internal migration costs in the early 2000s. The government has undertaken registration policy

reform and infrastructure investment that significantly reduced migration costs(Tombe and Zhu (2019)).

2.4 Theoretical framework

I build a two-country model which follows the preferences and entry in Melitz (2003) and combines Hsieh and Klenow (2009)'s definition of distortions on outputs and inputs and also includes imported intermediate input. I assume the two countries (Home(H) and Foreign(F)) are identical. Each country $i \in \{H, F\}$, is inhabited by L_i labour which is immobile across countries and inelastic supply. The endowment intermediate input X_i is tradable. In this model, firms employ both imported and domestic intermediate inputs, and labour to produce a unique variety of goods that are used for final consumption.

Preferences: The representative consumer in each country has CES preference with an elasticity of substitution $\sigma > 1$ over a continuum of goods indexed by ω.

$$U_i = \left[\int_{\omega \in \Omega_{ji}} q_{ji}^{\frac{\sigma-1}{\sigma}}(\omega) d\omega \right]^{\frac{\sigma}{\sigma-1}}, \quad i, j \in \{H, F\} \tag{2.1}$$

Where Ω_{ji} is the set of varieties produced in country j which are consumed in the country i, $q_{ji}(\omega)$ is the quantity ω consumed. The utility function 2.1 yields the CES demand function in country i for variety ω produced in country j:

$$q_{ji}(\omega) = P_i^{\sigma-1} E_i p_{ji}^{-\sigma}(\omega) \tag{2.2}$$

where E_i is the aggregate expenditure and P_i denotes the prices index

in country i. The corresponding price index is given by:

$$P_i = \left[\int_{\omega \in \Omega_{ji}} p_{ji}^{1-\sigma}(\omega) d\omega \right]^{\frac{1}{\sigma-1}}, i, j \in \{H, F\} \tag{2.3}$$

Production: There are potential entrants in two countries that can enter the market by paying a sunk entry cost of f_{ie} units of labour. Then these potential entrants are heterogeneous in terms of their productivity φ, which is drawn from a known Pareto distribution $F_{i,\varphi}(\varphi) = 1-(\varphi_{i,m}/\varphi)^{\eta_{i,\varphi}}$, where $\varphi_{i,m} > 0$ and $\eta_{i,\varphi} - \sigma - 1 > 0$ [1]. They also learn their idiosyncratic intermediate input wedges τ_{xii}, τ_{xji} on domestic and foreign intermediate inputs, and wedge τ_{yii} on output, respectively, which can be treated as a tax (> 1) or subsidy (< 1). Conceptually, I follow Hsieh and Klenow (2009) and Restuccia and Rogerson (2008)'s definition, these firm's specific subsidies and taxes are hypothetical but chosen as a representation of many factors that generate misallocation. I assume that the domestic and foreign input wedges and output wedges are drawn from the log-normal distribution which is independent of each other. Productivity also is assumed to be independent of wedges[2]. Let $\omega(\varphi, \tau_{xii}, \tau_{xji}, \tau_{yii})$ denote a firm's state vector and the corresponding cumulative density function for ω is given by $\Gamma_i(\omega) = F_{i,\varphi} \bigotimes F_{xii} \bigotimes F_{xji} \bigotimes F_{yii}$, where $\bigotimes$ means the tensor product.

After knowing their ω, firms decide whether to stay in or exit the market, then if a firm chooses to stay and operate, it faces strictly positive fixed costs f_{ii} units of labour ($f_{ii} = f_d$) when selling domestically and f_{ij} units of labour ($f_{ij} = f_f$) when exporting to foreign. Firms also need to

[1] The assumption of Pareto distribution is a common choice in the trade literature with heterogeneous firms. it makes the model tractable, and evidence shows that the firm size distribution is well fitted by Pareto distribution(Di Giovanni et al. (2011)).

[2] In Brooks and Wang (2016)'s paper, they assume the productivity is independent of variable trade distortions and fixed trade cost distortions, Costa-Scottini (2018) and Ho (2010) apply size-depend distortions, Bai et al. (2018) and Berthou et al. (2018) assume productivity and distortions are drawn from a joint distribution, and the correlation ρ = 0.8 using Chinese data.

pay positive costs $w_i f_{ix}$ when they decide to import foreign intermediate inputs. The presence of this importing intermediate input fixed cost is consistent with the evidence in Halpern et al. (2015) and Gopinath and Neiman (2014). They show that there is substantial heterogeneity in the import patterns of firms, about one-half of firms do not import at all, and firms which are larger are more likely to import, in Hungary and Argentine, respectively. Moreover, a firm that exporting final goods must pay iceberg trade cost (t_{ij}), where t_{ij} units of a good must be shipped in order for 1 unit to arrive at the destination, where $t_{ii} = 1$ and $t_{ij} > 1$ if $i \neq j$. I have a similar assumption on intermediate inputs iceberg trade costs (t_{xij}). I allow for $t_{ij} \neq t_{ji}$ and $t_{xij} \neq t_{xji}$, and bilateral and unilateral reduction in t_{ij} and t_{xij}, respectively, to investigate the effect of different trade liberalization.

Each firm ω in Home country produces a unique variety of goods using the Cobb-Douglas production function and α is the output elasticity with respect to intermediate inputs:

$$q = \varphi x^{\alpha} l^{1-\alpha} \tag{2.4}$$

where x is just domestic intermediate input (x_H) or composite intermediate input when deciding to use both domestic and imported inputs (x_F), l is the labour used in production. Composite input x combines domestic intermediate inputs and imported intermediate inputs, according to the CES form with the elasticity of substitution $\theta > 1$.

$$x = \left(x_H^{\frac{\theta-1}{\theta}} + x_F^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

where x_H, x_F are, respectively, the quantity of domestic and imported intermediate inputs used for production. The prices of the domestic and

foreign inputs are denoted p_{xi} and p_{xj}, and I assume that the firms are price takers in these input markets. Firms trade off the saving in marginal cost from importing foreign intermediate input against the importing fixed cost.

The effective price of the composite intermediate inputs x, if the firm chooses to import inputs, can be found by solving the cost-minimization problem associated with (2.4):

$$p_{xij}(\omega) = \left[(\tau_{xii}(\omega)p_{xi})^{1-\theta} + (t_{xji}\tau_{xji}(\omega)p_{xj})^{1-\theta}\right]^{\frac{1}{1-\theta}}$$

where p_{xi}, p_{xj} are the price of domestic and foreign intermediate input, respectively.

With distortions on outputs and domestic and foreign inputs, If a firm operates, it solves the following problem

$$max\pi_{p,q} = \sum_{j\in\{H,F\}} \left[\frac{p_{ij}q_{ij}}{\tau_{yii}} - t_{ij}MC_H^{ki} - w_i f_{ij}\right] \cdot 1_{ij}^{ki} - w_i f_{ix} \cdot 1_{ji}^{ki}, \qquad (2.5)$$

subject to the CES demand function

$$q_{ij} = E_j P_J^{\sigma-1} p_{ij}^{-\sigma}$$

where τ_{yii} is output distortion and τ_{xii}, τ_{xji} are domestic and foreign inputs distortions respectively. ki is the firms' type and will be defined in the following. 1_{ij}^{ki} takes the value of 1 if firms enter the export market and 1_{ji}^{ki} takes the value of 1 if firms use imported intermediate inputs.

Firms are monopolistic competitive. In the presence of output and input wedges, I can identify four types of firms in the model according

to the market they sell to and whether they use imported intermediate inputs: (1) Purely domestic firms: firms that use only domestic input and sell only domestically (indexed by k_{i1}), (2) Exporter only: firms that source domestically only, and sell final products to both domestic and foreign markets (indexed by k_{i2}), (3) Importer only: firms that source domestic and foreign, and sell only domestically (indexed by k_{i3}), (4) Two-way exporter-importer: firms source inputs from both home and foreign, and sell final products to both domestic and foreign markets (indexed by k_{i4}) [3].

A firm in country i charges an optimal domestic price that exhibits a constant mark-up above its marginal cost, $p_{ii}(\omega) = \frac{\sigma}{\sigma-1}\tau_{yii}MC_i(\omega)$, where $MC_i(\omega)$ denotes the marginal cost. The exporting price charged by firm ω is given by $p_{ij}(\omega) = \frac{\sigma}{\sigma-1}t_{ij}\tau_{yii}MC_i(\omega)$. The existence of exporting fixed cost (f_{ij}) and importing input fixed cost (f_{ix}) means that only a subset of firms can export and use imported intermediate input, respectively. The marginal cost of firm ω of type $k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$ in country i is given by:

$$MC_i^{k_i}(\omega) = \begin{cases} \frac{1}{\varphi}\left(\frac{\tau_{xii}p_{xi}}{\alpha}\right)^{\alpha}\left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} & \text{for} \quad k_i \in \{k_{i1}, k_{i2}\} \\ \frac{1}{\varphi}\left(\frac{p_{xij(\omega)}}{\alpha}\right)^{\alpha}\left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} & \text{for} \quad k_i \in \{k_{i3}, k_{i4}\} \end{cases} \tag{2.6}$$

where w_i is wage and p_{xij} is the effective price of composite intermediate input.

Equilibrium prices charged by firm(ω) in both market can be expressed as:

$$p_{ii}^{ki}(\omega) = \frac{\sigma}{\sigma-1}\tau_{yii}MC_i^{k_i}(\omega) \quad \text{for} \quad k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$$

$$p_{ij}^{ki}(\omega) = t_{ij}p_{ii}^{ki}(\omega) \quad \text{for} \quad k_i \in \{k_{i2}, k_{i4}\}$$

[3]The extreme cases, i.e., only using foreign intermediate is not included in the model.

The ex-post subsidy equilibrium revenues in the domestic and export market are given by:

$$r_{ii}^{ki}(\omega) = \frac{P_i^{\sigma-1}(p_{ii}^{k_i}(\omega))^{1-\sigma}}{\tau_{yii}} E_i \quad \text{for} \quad k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$$

$$r_{ij}^{ki}(\omega) = t_{ij}^{1-\sigma} \frac{E_j P_j^{\sigma-1}(p_{ii}^{k_i}(\omega))^{1-\sigma}}{\tau_{yii}} \quad \text{for} \quad k_i \in \{k_{i2}, k_{i4}\}$$

The optimal profits in each market are a constant proportion of revenues minus the fixed cost:

$$\pi_{ii}^{ki}(\omega) = \frac{r_{ii}^{ki}(\omega)}{\sigma} - w_i f_{ii} \quad , \pi_{ij}^{ki}(\omega) = \frac{r_{ij}^{ki}(\omega)}{\sigma} - w_i f_{ij} \quad \text{for} \quad k_i \in \{k_{i1}, k_{i2}\}$$

$$\pi_{ii}^{ki}(\omega) = \frac{r_{ii}^{ki}(\omega)}{\sigma} - w_i f_{ii} - w_i f_{ix} \quad , \pi_{ij}^{ki}(\omega) = \frac{r_{ij}^{ki}(\omega)}{\sigma} - w_i f_{ij} \quad \text{for} \quad k_i \in \{k_{i3}, k_{i4}\}$$

The productivity cutoffs for serving the domestic market ($\varphi_{ii}^{*,k_i}(\tau_{xii}, \tau_{xji}, \tau_{yii})$) and foreign market ($\varphi_{ij}^{*,k_i}(\tau_{xii}, \tau_{xji}, \tau_{yii})$) are defined by the zero-profit condition. These cutoff productivity levels are given by:

$$\varphi_{ii}^{*,k_i}(\tau_{xii}, \tau_{xji}) = \begin{cases} \left(\frac{\sigma w_i f_{ii}}{E_i P_i^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} \left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\tau_{xii} p_{xi}}{\alpha}\right)^{\alpha} \tau_{yii}^{\frac{\sigma}{\sigma-1}} & \text{for} \quad k_i \in \{k_{i1}, k_{i2}\} \\ \left(\frac{\sigma w_i (f_{ii}+f_{ix})}{E_i P_i^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} \left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{p_{xij}}{\alpha}\right)^{\alpha} \tau_{yii}^{\frac{\sigma}{\sigma-1}} & \text{for} \quad k_i \in \{k_{i3}, k_{i4}\} \end{cases} \tag{2.7}$$

$$\varphi_{ij}^{*,k_i}(\tau_{xii}, \tau_{xji}) = \begin{cases} \left(\frac{\sigma w_i f_{ij}}{E_j P_j^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} t_{ij} \left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\tau_{xii} p_{xi}}{\alpha}\right)^{\alpha} \tau_{yii}^{\frac{\sigma}{\sigma-1}} & \text{for} \quad k_i = k_{i2} \\ \left(\frac{\sigma w_i f_{ij}}{E_j P_j^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} t_{ij} \left(\frac{w_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{p_{xij}}{\alpha}\right)^{\alpha} \tau_{yii}^{\frac{\sigma}{\sigma-1}} & \text{for} \quad k_i = k_{i4} \end{cases} \tag{2.8}$$

Like the assumption in Melitz (2003) and Bai et al. (2019), consumer love of variety, a fixed operating cost, and the fixed exporting cost, mean that firms would never export without also serving the domestic market. Hold wedges τ_{xii}, τ_{xji} constant, for types k_{i2} and k_{i4}, the ratio $\varphi_{ij}^{*,k_i}/\varphi_{ii}^{*,k_i}$

is a constant and is greater than 1 so long as $\frac{t^{\sigma-1}f_{ij}}{f_{ii}}\frac{P_i^{\sigma-1}E_i}{P_j^{\sigma-1}E_j} > 1$. Holding distortions constant, the more productive firms are more likely to export. Taking the partial derivative of the cutoff productivity with respect to domestic input distortion τ_{xii} holding τ_{xji} constant. $\frac{\partial\varphi_{ii}^{*,k_i}}{\partial\tau_{xii}}|_{\tau_{xji}} > 0$ and $\frac{\partial\varphi_{ij}^{*,k_i}}{\partial\tau_{xii}}|_{\tau_{xji}} > 0$ means that firms that have relatively high subsidies (lower τ_{xii}) on domestic intermediate inputs are more likely to operate and export.

For given realization of productivity and three wedges, the total profits for firms of types for k_{i2} and k_{i3} are given by:

$$\pi_i^{k_{i2}}(\omega) = \pi_{ii}^{k_{i2}}(\omega) + \pi_{ij}^{k_{i2}}(\omega) \quad , \quad \pi_i^{k_{i3}}(\omega) = \pi_{ii}^{k_{i3}}(\omega) + \pi_{ij}^{k_{i3}}(\omega)$$

then $\left(\frac{p_{xij}}{\alpha}\right)^{\alpha(1-\sigma)} - \left(\frac{\tau_{xii}p_{xi}}{\alpha}\right)^{\alpha(1-\sigma)} \lesseqgtr \frac{\sigma w_i f_{ix}\tau_{yii}}{(E_i P_i^{\sigma-1} + t_{ij}^{1-\sigma}E_j P_j^{\sigma-1})(\varphi)^{\sigma-1}(\frac{w_i}{1-\alpha})^{(1-\alpha)(1-\sigma)}}$

A firm prefers type k_{i2} if the value of the left-hand side is less than the right-hand side. Otherwise, it sources from both markets and sells domestically. Intuitively, firms with relatively high subsidies on domestic intermediate inputs will choose to use only domestic input and export. Taking the partial derivative of the cutoff productivity with respect to domestic input distortion τ_{xii} holding τ_{xji} constant. $\frac{\partial\varphi^{*,k_{i2}=k_{i3}}}{\partial\tau_{xii}}|_{\tau_{xji}} > 0$ means that given realization of other variables and foreign intermediate input wedge, the opportunity cost of using foreign intermediate inputs is higher for firms that have relatively high subsidy on domestic intermediate inputs.

The minimum productivity necessary for a firm of type k_i in country i to operate profitably can be expressed as:

$$\varphi_{ii}^*(\tau_{xii}, \tau_{xji}) = \min_{k_i}\{\varphi_{ii}^{*,k_i}\} \quad \text{for} \quad k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$$

where $\varphi_{ii}^{*,k_i} = \{\varphi : \pi_{ii}^{k_i}(\omega) = 0\}$.

The minimum productivity necessary for a firm of type k_i in country i to serving the Foreign market profitably can expressed as:

$$\varphi^*_{ij}(\tau_{xii}, \tau_{xji}) = \min_{k_i}\{\varphi^{*,k_i}_{ij}\} \quad \text{for} \quad k_i \in \{k_{i2}, k_{i4}\}$$

where $\varphi^{*,k_i}_{ij} = \{\varphi : \pi^{k_i}_{ij}(\omega) = 0\}$.

Free entry condition: In an equilibrium with positive entry, the free entry condition equates the expected profit after successful entry to the sunk entry cost in terms of labour, which is given by:

$$\sum_{k_i}\left[\iiiint_{\varphi^*_{ii}(\tau_{xii},\tau_{xji})} \pi^{k_i}_{ii}(\omega))\Gamma_i(\omega)d\varphi d\tau_{yii}d\tau_{xii}d\tau_{xji}\right] + \sum_{k_i}\left[\iiiint_{\varphi^*_{ij}} \pi^{k_i}_{ij}(\omega)\Gamma_i(\omega)d\varphi d\tau_{yii}d\tau_{xii}d\tau_{xji}\right] = \delta w_i f_{ie} \quad (2.9)$$

The first term is the expected profits from domestic sales for all types of firms conditional on entry. The second term is the expected profits from exporting sales conditional on exporting, multiplied by the probability of exporting. I define χ^*_{ii} [4] is the probability of successful entering the market, and χ^*_{ij} [5] denotes the probability of exporting conditional on successful entry.

In stationary equilibrium, the mass of producing firms (M_i) exit equals the mass of potential entrants (M_{ie}) multiplied by the probability of entry:

$$\delta M_i = \chi^*_{ii} M_{ie}$$

Labour used to pay the sunk entry costs by the mass of entrants is given

[4] $\chi^*_{ii} = 1 - \Gamma_i(\varphi^*_{ii}(\tau_{yii}, \tau_{xii}, \tau_{xji}))$
[5] $\chi^*_{ij} = \frac{1-\Gamma_i(\varphi^*_{ij}(\tau_{yii},\tau_{xii},\tau_{xji}))}{1-F_i(\varphi^*_{ii}(\tau_{yii},\tau_{xii},\tau_{xji}))}$

by:

$$L_{ie} = M_{ie} f_{ie}$$

Labour used in production by individual firm(ω) can be expressed as:

$$l_{p_{ii}}^{k_i}(\omega) = \frac{(1-\alpha) MC_i^{k_i}(\omega) q_{ii}^{k_i}(\omega)}{w_i} \quad \text{for} \quad k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$$

$$l_{p_{ij}}^{k_i}(\omega) = \frac{(1-\alpha) MC_i^{k_i}(\omega) t_{ij} q_{ij}^{k_i}(\omega)}{w_i} \quad \text{for} \quad k_i \in \{k_{i2}, k_{i4}\}$$

thus the total labour used in production can be expressed as:

$$L_{ip} = M_i \left[\sum_{k_i} \int l_{p_{ii}^{k_i}(\omega)} + l_{p_{ij}^{k_i}(\omega)} d\Gamma_i(\omega) \right]$$

Total labour used in fixed costs is given by:

$$L_{if} = M_i \left[\sum_{k_i} \int l_{l_{if}^{k_i}(\omega)} d\Gamma_i(\omega) \right]$$

where $l_{if}^{k_i}$ denotes labour used in fixed costs by a firm (ω) [6].

labour market clearing condition:

$$L_i = L_{ie} + L_{if} + L_{ip}, \quad i \in \{H, F\} \tag{2.10}$$

The domestic intermediate inputs used by an individual firm in country

[6] labour used in fixed costs can be expressed as:

$$l_{if}^{k_i} = \begin{cases} f_{ii} & \text{for} \quad k_i = k_{i1} \\ f_{ii} + f_{ij} & \text{for} \quad k_i = k_{i2} \\ f_{ii} + f_{ix} & \text{for} \quad k_i = k_{i3} \\ f_{ii} + f_{ij} + f_{ix} & \text{for} \quad k_i = k_{i4} \end{cases}$$

i can be expressed as:

$$x_{ii}^{k_i}(\omega) = \begin{cases} \frac{\alpha}{\tau_{xii}p_{xi}} E_i P_i^{\sigma-1} (\frac{\sigma-1}{\sigma})^{\sigma} (MC_i^{k_i}(\omega))^{1-\sigma} & \text{for} \quad k_i = k_{i1} \\ \frac{\alpha}{\tau_{xii}p_{xi}} (E_i P_i^{\sigma-1} + t_{ij}^{1-\sigma} E_j P_j^{\sigma-1}) (\frac{\sigma-1}{\sigma})^{\sigma} (MC_i^{k_i}(\omega))^{1-\sigma} & \text{for} \quad k_i = k_{i2} \\ (\frac{p_{xij}}{\tau_{xii}p_{xi}})^{\theta} x_i^{k_i}(\omega) & \text{for} \quad k_i \in \{k_{i3}, k_{i4}\} \end{cases}$$

where $x_i^{k_i}$ denotes the quantity of composite intermediate input.[7]

The foreign intermediate inputs used by an individual firm in the country i can be expressed as:

$$x_{ji}^{k_i}(\omega) = \begin{cases} 0 & \text{for} \quad k_i \in \{k_{i1}, k_{i2}\} \\ (\frac{p_{xij}}{t_{xji}\tau_{xji}p_{xj}})^{\theta} x_i^{k_i}(\omega) & \text{for} \quad k_i \in \{k_{i3}, k_{i4}\} \end{cases}$$

Intermediate inputs market clearing condition:

$$X_i = M_i \sum_{k_i} \int x_{ii}^{k_i}(\omega) d\Gamma_i(\omega) + t_{xij} M_j \sum_{k_j} \int x_{ij}^{k_j}(\omega) d\Gamma_j(\omega) \quad i, j \in \{H, F\} \tag{2.11}$$

where the first term on the right-hand side is the quantity of used domestic intermediate input in country i, and the second term is the quantity of intermediate input imported by foreign firms from country i.

The aggregate income consistency in country i:

$$E_i = w_i L_i + p_{xi} X_i + T_i, \quad i \in \{H, F\} \tag{2.12}$$

where T_i is the amount of lump-sum transfers received from the government, which is given by:[8]

[7] $x_i^{k_i} = \begin{cases} \frac{\alpha}{p_{xij}} E_i P_i^{\sigma-1} (\frac{\sigma-1}{\sigma})^{\sigma} (MC_i^{k_i}(\omega))^{1-\sigma} & \text{for} \quad k_i = k_{i3} \\ \frac{\alpha}{p_{xij}} (E_i P_i^{\sigma-1} + t_{ij}^{1-\sigma} E_j P_j^{\sigma-1}) (\frac{\sigma-1}{\sigma})^{\sigma} (MC_i^{k_i}(\omega))^{1-\sigma} & \text{for} \quad k_i = k_{i4} \end{cases}$

[8] Bai et al. (2018) and Brooks and Wang (2016) assume the government budget is

$$T_i = M_i \Bigg[\sum_{k_i} \int \Bigg(\Bigg(1 - \frac{1}{\tau_{yii}} \Bigg) (p_{ii}^{ki} q_{ii}^{ki} + p_{ij}^{ki} q_{ij}^{ki}) + (\tau_{xii} - 1) p_{xi} x_{ii}^{k_i}(\omega) + (t_{xji}\tau_{xji} - 1) p_{xj} x_{ji}^{k_i}(\omega) \Bigg) d\Gamma_i(\omega) \Bigg] \tag{2.13}$$

Balanced trade condition: More specifically, we use k_{H2}, k_{H3}, k_{H4} represent the firms' type in Home country, and k_{F2}, k_{F3}, k_{F4} represent the firms' type in Foreign country

$$M_H \left[\sum_{k_H \in \{k_{H2}, k_{H4}\}} \int r_{HF}^{k_H}(\omega) d\Gamma_H(\omega) \right] + M_F \left[\sum_{k_F \in \{k_{F3}, k_{F4}\}} \int t_{xhf} p_{xH} x_{HF}^{k_F}(\omega) d\Gamma_F(\omega) \right] = M_F \left[\sum_{k_F \in \{k_{F2}, k_{F4}\}} \int r_{FH}^{k_F}(\omega) d\Gamma_F(\omega) \right] + M_H \left[\sum_{k_H \in \{k_{H3}, k_{H4}\}} \int t_{xfh} p_{xF} x_{FH}^{k_H}(\omega) d\Gamma_H(\omega) \right] \tag{2.14}$$

Where the first term is the total value of Home firms' final goods exporting, the second term is the total value of Home input exporting, the third term is the total value of Foreign firms' final goods exporting, and the last term is the total value of Foreign inputs exporting.

Equilibrium: Normalizing the Home country wage rate to 1, there are nine equations, the free entry condition 2.9 along with its Foreign counterpart, the labour market clear condition 2.10 and its Foreign counterpart, the intermediate input clear condition 2.11 and its Foreign counterpart, the aggregate income consistency condition 2.12 and its Foreign counterpart, and balanced trade condition 2.14. These nine equations yield the equilibrium consisting of nine unknown endogenous variables $\{P_H, P_F, E_H, E_F, M_H, M_F, w_F, p_{xH}, p_{xF}\}$.

balanced, so the total subsidy or tax is zero.

In the equilibrium, following Hsieh and Klenow (2009), the marginal revenue product of labour $MRPL$ in country i is given by:

$$MRPL_i(\omega) = w_i \tau_{yii}$$

the marginal revenue product of intermediate input $MRPX$ is given by:

$$MRPX_i(\omega) = \begin{cases} \tau_{yii}\tau_{xii}p_{xi} & \text{for} \quad k_i \in \{k_{i1}, k_{i2}\} \\ \tau_{yii}p_{xij} & \text{for} \quad k_i \in \{k_{i3}, k_{i4}\} \end{cases}$$

Intuitively, the after-tax marginal revenue products are heterogeneous under intermediate input distortions. $TFPR$ is revenue based on TFP, which is proportional to a geometric average of the firm's marginal revenue products of labour and intermediate inputs:

$$TFPR_i(\omega) \propto (MRPX_i(\omega))^{\alpha}(MRPL_i(\omega))^{1-\alpha}$$

The aggregate TFP in country i is given by:

$$TFP_i = \Delta_i M_i \left[\sum_{ki} \left[\iiiint_{\varphi_{ii}^{*,k_i}(\tau_{xii},\tau_{xji})} \varphi^{\sigma-1} \left(\frac{\overline{MRPX_i}}{MRPX_i(\omega)} \right)^{(\sigma-1)(\alpha)} \times \left(\frac{\overline{MRPL_i}}{MRPL_i(\omega)} \right)^{(\sigma-1)(1-\alpha)} d\Gamma(\omega) \right] \right] \tag{2.15}$$

Where $k_i \in \{k_{i1}, k_{i2}, k_{i3}, k_{i4}\}$; Δ_i is constantly determined by model parameters in country i, and $\overline{MRPX}$ is the country-wide marginal revenue product of intermediate inputs. This equation shows that the sources that affect the aggregate TFP can be captured by M_i, cutoff productivity $\varphi_{ii}^{*,k_i}(\tau_{xii}, \tau_{xji})$ and the dispersion of marginal revenue product of interme-

diate inputs ($\left(\frac{\overline{MRPX_i}}{MRPX_i(\omega)}\right)$) and labour ($\left(\frac{\overline{MRPL_i}}{MRPL_i(\omega)}\right)$) caused by output and input distortions. Changes in intermediate input variable trade cost (t_{xji}) affect the aggregate TFP through the entry, selection in exporting and importing, and misallocation. Intuitively, a reduction in unilateral (t_{xji}) or bilateral (t_{xji} and t_{xij}) intermediate input tariff reduces the prices of inputs, more productive firms and relatively highly-subsided firms increase at the cost of less productive and relatively highly-taxed firms.

Bring input distortions to data

In the previous part, we derived a relationship between sets of parameters. Obviously, the trade parameters are not directly observable, so it is difficult to bring the results to data. In this section, we show how to drive the welfare-related statistics that summarise the distribution of input distortions.

Conceptually, we can follow Hsieh and Klenow (2009) and Chen and Irarrazabal (2015)'s method of decomposition for the aggregate TFP in the Home country as:

$$\begin{aligned}\log TFP = \log(TFP^e) + \frac{1}{\sigma-1}\log(M) + \frac{1}{2}(\sigma-1)\operatorname{Var}(\log(\varphi)) \\ -\frac{1}{2}\sigma\operatorname{Var}(\log(\tau_{yHH})) - \frac{1}{2}\alpha(\alpha(\sigma-1)+1)\operatorname{Var}(\log(p_{xHF})) \\ + \alpha\sigma\operatorname{Cov}(\log(\tau_{yHH}), \log(P_{xHF}))\end{aligned} \quad (2.16)$$

where $log(TFP^e)$ denotes the aggregate TFP without any distortions, $Var(log(\tau_{yHH}))$ represents the output distortions, and $Var(log(p_{xHF})$ captures the domestic and foreign distortions that drive the domestic-foreign input ratio away from the first-best outcome.

$$Var(log(p_{xHF})) = Var(log(\tau_{xHH})) + \left(\frac{\theta-1}{\theta}\right)^2 Var\left(log\left[1 + \underbrace{(\frac{p_{xF}}{p_{xH}})^{\frac{\theta}{\theta-1}}(\frac{t_{xFH}\tau_{xFH}}{\tau_{xHH}})^{\frac{\theta}{\theta-1}})}_{\text{Import intensity}}\right]\right) + \left(\frac{\theta-1}{\theta}\right)^2 2Cov(\Phi) \quad (2.17)$$

where $\Phi = log(\tau_{xH}), log\left[1 + (\frac{p_{xF}}{p_{xH}})^{\frac{\theta}{\theta-1}}(\frac{t_{xFH}\tau_{xFH}}{\tau_{xHH}})^{\frac{\theta}{\theta-1}})\right]$, and $Var(log(\tau_{xHH}))$ captures the domestic input distortions.

Moreover, from the above equation 2.17, we can find that the distribution of the price of the composite intermediate input depends crucially on the variation in the term $(\frac{p_{xF}}{p_{xH}})^{\frac{\theta}{\theta-1}}(\frac{t_{xFH}\tau_{xFH}}{\tau_{xHH}})^{\frac{\theta}{\theta-1}}$ which is the exact measure of the firm-level import intensity (Brooks and Wang (2016)). In practice, we can easily get the firm-level import intensity from the observable data. Practically, we can define the firm-level import intensity ($Iiint$) as follows:

$$\begin{aligned} Iiint &= \frac{t_{xFH}\tau_{xFH}p_{xF}x_{FH}}{t_{xFH}\tau_{xFH}p_{xF}x_{FH} + \tau_{xHH}p_{xH}x_{HH}} \\ &= \frac{(t_{xFH}\tau_{xFH}p_{xF})^{1-\theta}}{(t_{xFH}\tau_{xFH}p_{xF})^{1-\theta} + (\tau_{xHH}p_{xH})^{1-\theta}} \end{aligned} \quad (2.18)$$

2.5 The data

This research uses two databases[9]. The first database for Chinese firms is from the Annual Survey of Industrial Firms collected by the Chinese National Bureau of Statistics (NBS). The second database is the transaction-level customs data from the Chinese General Administration of Customs (CGAC). With the merged database of NBS data and customs data, we are able to analyze the effect of trade liberalization on Chinese economic performance in much more detail.

The NBS firm-level data covers non-state-owned firms with annual sales above 5 million Chinese yuan (or equivalently, 600,000 US dollars approximately) before 2011, 20 million RMB after 2011 (approximately 3 million USD in 2011), and all of the state-owned enterprises. This database contains firm-level information, including firm identification (e.g., Firm ID, firm name, starting year, and location), ownership type, address, telephone number, the net value of fixed assets, employment, gross output, value-added, wages, industry, and various financial variables. To clean this Chinese NBS data, we follow these processes and drop odd observations: (i) that report missing or negative values on total sales, employment, fixed asset, total revenue, intermediate inputs, and export; (ii) that hire labour less than 8; (iii) that have values of total sales less than corresponding values of exporting (Cai and Liu (2009); Yu (2015); Zhang et al. (2023)). We follow the **?**'s strategy to conclude the data in 2010 from our firm-level analysis. Because the number of firms in the NBS data is substantially smaller than those in adjacent years and no explanation has been offered by the Chinese NBS.

[9]Acknowledgments: I would like to express our gratitude to my supervisor Zhihong Yu for generously sharing the NBS data and Customs data used in this research. This data contribution was instrumental in my analysis and greatly enhanced the quality and scope of my study.

Customs data includes export and import flow from 2000 to 2013 at the HS eight-digit level. For each international transaction, the customs data records detailed information including firm identification information, import and export values, quantities, products, sources and destinations, and each commodity's HS code[10].

The time span of this merged panel data used in our research is from 2000 to 2013. We follow the practice of Yu (2015) to match NBS data and customs data. However, we can not merge these two databases by using the uniquely firm code, which is different in NBS and customs data. First, we use the firm's name and year to merge these databases. After this step, we further use the firm's specific postal code and the last seven digits of a phone number to match the samples that are not matched in the first step. This can effectively solve the problem that the same firm has two different names in NBS data and customs data. In the NBS database, all the variable values are recorded in thousand Chinese Yuan, but customs data reports the trade values in one US dollar. We convert the trade values in customs data to thousand Chinese Yuan to keep the consistency. In addition, we dropped observations that export intensity or import share was greater than 1, which is crucial in this research.

The final sample used in this chapter consisted of 244,127 firms, with exporting and importing firms accounting for 28.9% and 14.3% of observations, respectively, in the year 2005. Table 2.1 provides summary statistics for the NBS firm-level and matched data. Figure 2.1 illustrates the input import intensity of importers, who primarily import intermediate inputs used for the production process as opposed to final goods.

[10]This customs dataset has been widely used in research by Yu (2015); Zhang et al. (2023); Manova and Yu (2016); Zhao et al. (2022)

Figure 2.1: Import intensity among importers

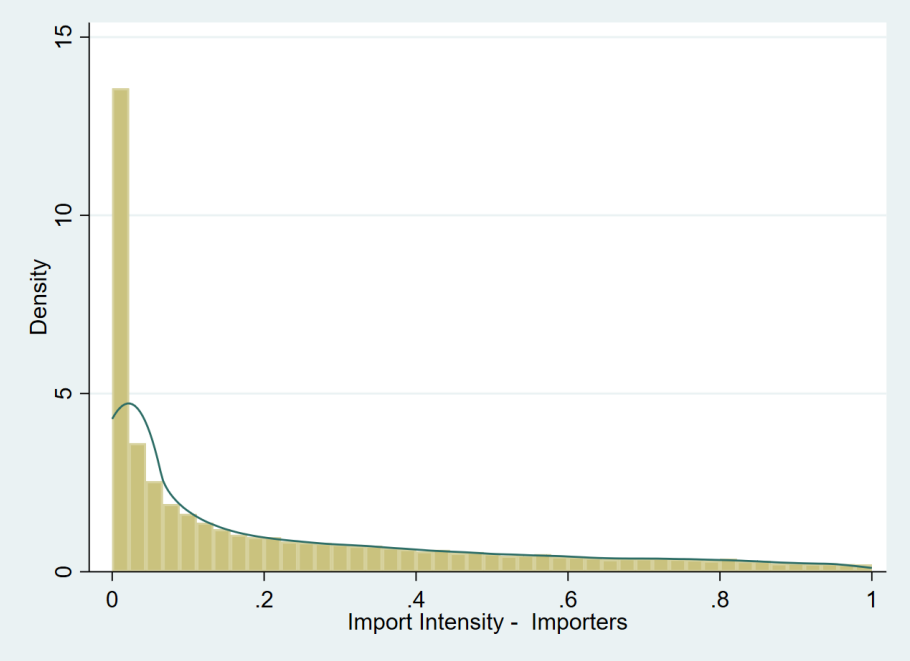


Table 2.1: Summary statistics: firm performance (year 2005)

	Full sample	Non-Importer&Non-Exporter(k1)	Exporter &Non-Importer(k2)	Non-Exporter& Im-porter(k3)	Exporter& Im-porter(k4)
Log labour	5.37	2.18	2.51	2.52	2.75
Log sales	4.91	4.66	5.02	5.27	5.37
Log sales per worker	2.55	2.48	2.52	2.75	2.62
Log Value added	4.33	4.11	4.44	4.68	4.75
Log VA per worker	1.96	1.93	1.93	2.16	2
(log) Inputs	4.81	4.56	4.92	5.18	5.27
Share of importers	0.143	0	0	1	1
Share of exporters	0.289	0	1	0	1
Number of observations	244,127	164,328	44,655	9,131	26,013

Note: All amounts are expressed in thousand Chinese Yuan.

2.6 Quantitative analysis

2.6.1 Calibration

This section describes the procedure used to calibrate this model to the Chinese data. Specifically, I assign values to the endowments, preferences, and parameters of my model and produce the moments to match the features of the distributions of the input import intensity of the Chinese data.

I assume that both Home and Foreign countries are identical in terms of their labour and input endowments, preferences, the distributions of firms' productivity, and the distortions as well as the parameters in the analysis. I allow for four dimensions of firm-level heterogeneity to generate the distribution of the import intensity. Then, firms in both countries draw productivity, domestic input distortion, foreign input distortion, and output distortions from the same distributions.

I also assume that the fixed entry, operating, importing and exporting costs have the following relationship that $fe_h = fe_f$, $f_{hh} = f_{ff}$, $f_{hf} = f_{fh}$, $f_{hx} = f_{fx}$, $t_{hf} = t_{fh}$ and $t_{xfh} = t_{xhf}$. I follow Melitz and Polanec (2015) and Defever and Riaño (2017) the assumption and normalize the domestic operating fixed cost f_{hh} to 1 since scaling up or down all fixed costs by the same level in the model does not affect the aggregate variables of interest.

The Home and Foreign labour L_h, L_f, and the input endowment x_h, x_f are normalized to 1. I set the elasticity of substitution between final goods σ to be 3, the one taken in Hsieh and Klenow (2009), Defever and Riaño (2017) and Bai et al. (2019). Also, I set the elasticity of substitution

between domestic and foreign intermediate inputs θ to be 3 [11].

As is standard, I allow firms to differ in productivity, and follow a Pareto distribution with lower bound 1 and shape parameter α. I set $\alpha = 2.713$ following Defever and Riaño (2017)'s estimation. Similarly to other parameters, the iceberg trade cost of final goods incurred is assumed to be the same for domestic and foreign countries: $t_{HF} = t_{FH}$. Generally, the final goods iceberg trade costs are usually calibrated to match the country's average final goods export intensity. However, this research pays more attention to the behavior of the input trade, so I assign $t_{HF} = t_{FH} = 1.5$ following Bai et al. (2019)'s estimation with Chinese data, which is similar to the estimate of 1.7 in Anderson and Van Wincoop (2003).

The remaining parameters are calibrated jointly to match the model moments and their data counterparts, and I choose to minimize the percentage differences with the equal weight between the moments in the model and in the data. Clearly, each parameter value affects the general equilibrium and other moments. However, there is some underlying relationship between certain parameters and moments. My calibration strategy is as follows.

There is the fixed cost of exporting final goods f_{hf}, the fixed cost of importing inputs f_{hx}, the fixed cost of entry f_e, the iceberg trade costs of input trade, and the parameters governing the distribution of firm-specific domestic input, foreign input, and output distortions. I assume that the latter are drawn from independent log-normal distributions with parameters $(\mu_{\tau xh}, \sigma^2_{\tau xh})$, $(\mu_{\tau xf}, \sigma^2_{\tau xf})$and $(\mu_{\tau y}, \sigma^2_{\tau y})$ respectively, which denote the mean and variance of the normal distribution for each distortion. I assume $\mu_{\tau y} = -0.5\sigma^2_{\tau y}$, $\mu_{\tau xf} = -0.5\sigma^2_{\tau xf}$ and $\mu_{\tau xh} = -0.5\sigma^2_{\tau xh}$ so that output and input distortion have a mean of 1, respectively.

[11] In Halpern et al. (2015)'s paper, they estimate the elasticity of substitution between domestic and foreign inputs is $\theta \in [3.05; 6.07]$ using Hungarian data.

I calibrate the distribution of import intensity which is determined by parameters of input distortions and iceberg cost of inputs, as $Iiint = \frac{(t_{xfh}p_{xf})^{1-\theta}}{(t_{xfh}\tau_{xf}p_{xf})^{1-\theta}+(\tau_{xh}P_{xh})^{1-\theta}}$. The moments we target are the 50th, 75th and 90th percentiles of the distribution of import intensity as well as the fraction of exporting (28.9%), import participation (14.3%) the ratio of the average size of importers and non-importers which are affected by the selection effects through the distortions and the fixed costs. Table 2.2 summarises the parameters used to solve the model. This model fits the distribution of import intensity well.

Table 2.2: Calibration model with heterogeneous distortions

Panel (A) : Structural parameters			
Description	**Parameters**		**Value**
Assigned parameters			
Elasticity of substitution between final goods	σ		3
Elasticity of substitution between inputs	θ		3
The intermediate input share of revenues	α		0.514
labour size (L)	Lh		1
Endowment of inputs (Xh)	Xh		1
Shape parameter productivity distribution	a_ϕ		2.713
Scale parameter productivity distribution	ϕ_{minh}		1
Iceberg trade cost - final goods	t_hf		1.5
Fixed cost - domestic sales	f_hh		1
Calibrated parameters			
Fixed cost of entry	fe		8.01
Fixed cost - exporting final goods	f_hf		1.94
Fixed cost - importing inputs	f_hx		0.63
Iceberg trade cost - input	t_xfh		3.38
Domestic inputs distortions	$(\ln(\tau_{xh}))$	$N(\mu,\sigma)$	(0.3238, -0.5*0.3238)
Foreign inputs distortions	$(\ln(\tau_{xf}))$	$N(\mu,\sigma)$	(0.0977, -0.5*0.0977)
Output distortions	$(\ln(\tau_{xy}))$	$N(\mu,\sigma)$	(0.3697, -0.5*0.3697)
Panel (B) : Moments			
	Data		Model
Fraction of exporting	0.289		0.314
Fraction of importing	0.143		0.205
average import intensity - importers	0.224		0.211
average ratio of importers/non-importers	3.757		3.557
Percentiles of import intensity - importers - 50th	0.102		0.132
- 75th	0.367		0.314
- 90th	0.666		0.482

2.6.2 Quantitative results

In this section, I will show the quantitative effects of input trade when accounting for the input and output distortions.

Figure 2.2 shows the changes of shares of corresponding types of firms with the reduction in input iceberg trade cost: the share of Purely domestic firms(indexed by k_{i1}) and Exporter only (indexed by k_{i2}) decrease; the share of Importer only (indexed by k_{i3}) and Exporter & Importer (indexed by k_{i4}) increase.

Figure 2.2: Shares of four types of firms (open economy distorted case)

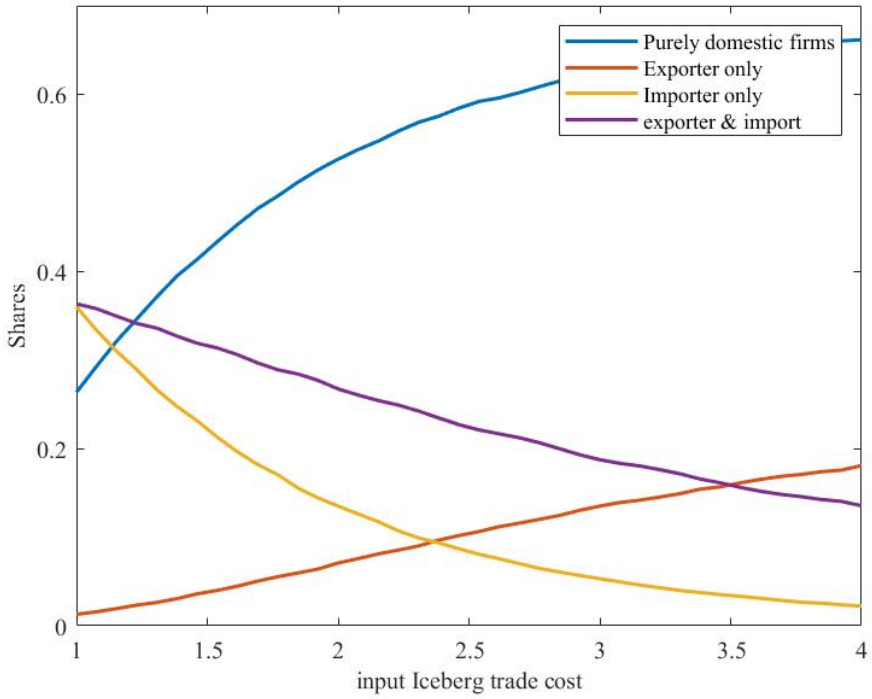


Figure 2.3 shows the level of aggregate TFP against the input iceberg trade cost. There are four scenarios: the open economy with and without distortions, and the closed economy with and without distortions. In the closed economy, I assume the Home country has the calibrated output and domestic input distortions and follows the Hsieh and Klenow (2009)'s analysis. The difference is that I include the selection mechanism induced by entry and exit. In the open economy, I add the reduction of input iceberg trade costs into the analysis. From Figure 2.3, I can show that: (1) the aggregate TFP for the cases with output and both domestic and foreign distortions is significantly smaller than that for the case without any distortions in both open and closed economy; (2) input trade liberalization leads to gains in the aggregate TFP in both efficient and distorted open economy cases. The former results are consistent with findings in Hsieh and Klenow (2009), Brooks and Wang (2016) and Bai et al. (2019) that distortions decrease the aggregate TFP. The latter is consistent with Ding et al. (2016)'s finding that import penetration reduces productivity dispersion through competition-induced resource reallocation within industries.

We focus on two kinds of counterfactuals: (1) Open relative to autarky and (2) decrease in the input iceberg trade cost by 5%, 10%, and 20%. Table 2.3 contains the results, from which we can draw two main conclusions.

First, from panel (A) columns (1)-(2) show that the aggregate TFP in the open economy is 12.71% and 17.71% higher than that in the closed economy for efficient case (without distortions) and distorted case (with calibrated distortions), respectively. In terms of the mass of operating firms, the results in the closed economy are 7.97% and 11.66% higher than corresponding values in the open economy for efficient and distorted cases, respectively.

Second, results in panel (B) column (2) presents that in the open economy with the calibrated parameters of distortions the aggregate TFP increase by 0.63%, 1.28%, and 3.11% when changing the calibrated value of input iceberg trade cost by 5%, 10%, and 20%, respectively. We find a similar pattern in the efficient cases but with a lower level of effects.

Overall, we can get the results from Figure 2.3 and Table 2.3 that: (1) with other factors fixed, the aggregate TFP in the open economy is higher than that in the closed economy; (2) the aggregate TFP of the efficient case is higher than that of the distorted case with calibrated distortions; (3) aggregate TFP in both efficient case and distorted cases are increasing with the reduction of the input iceberg trade cost; (4) The elasticity of aggregate TFP with respect to the input iceberg trade cost is higher in the distorted case than that in the efficient case. Bear these in mind, we then move to the next counterfactuals.

The output and input distortions are important determinants of the gains of trade and aggregate TFP changes. I may turn off each distortion step by step and show the changes of aggregate TFP and the corresponding elasticity against the reduction of the input iceberg trade cost in figure 2.4. The more details are as follows: (1) efficient case without any distortions; (2) distorted case with output, domestic, and foreign input distortions; (3) distorted case with foreign input and output distortions; (4) distorted case with domestic input and output distortions; (5) distorted case with domestic and foreign input distortions; (6) distorted case with only output distortion; (7) distorted case with only foreign input distortion; (8) distorted case with only domestic input distortion.

From figure 2.4, the obvious result of the left panel is that the reduction of the input iceberg trade costs increases the aggregate TFP for all

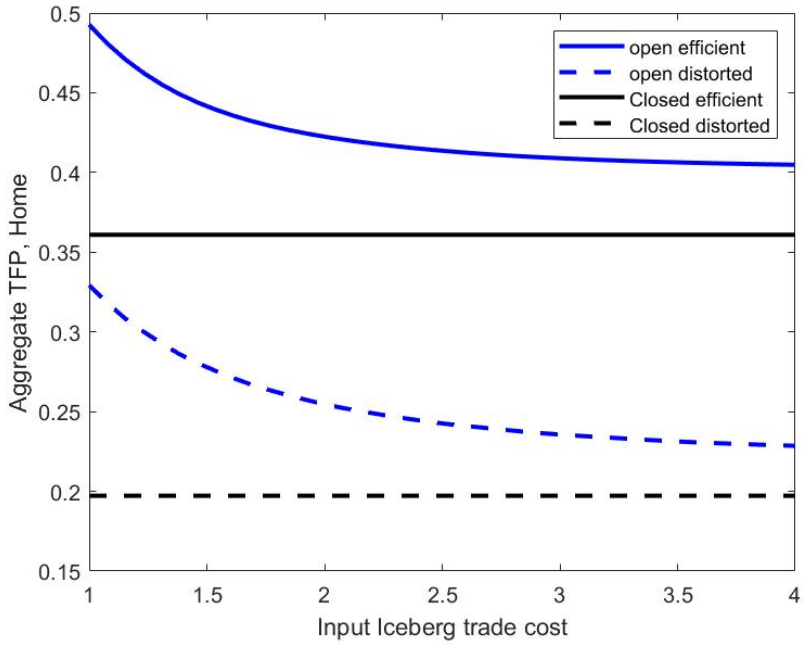
scenarios. With fixed input iceberg trade cost, the distortions significantly decrease the aggregate TFP. More specifically, the domestic input distortion contributes to the most aggregate TFP loss compared to the efficient case. The right panel of this figure reports that the elasticity of aggregate TFP with respect to the reduction of the input iceberg trade cost is positive and larger under distorted cases than in the distortion-free case, except for the distorted case with only foreign distortion. These results are consistent with the findings shown in Table 2.3.

Not surprisingly, Table 2.4 also shows the aggregate TFP loss in distorted cases relative to the efficient case. The majority of the loss is contributed by domestic input distortion (-23.6%) and output distortion (-22.6%). The foreign distortion contributes a small effect on the TFP loss when the input iceberg trade cost is relatively high. Table 2.4 also shows that the elasticity belonging to the efficient case is lower than that of distorted cases with three distortions, with only domestic input distortion and with only output distortion.

This result is very interesting for us to understand. Intuitively, With the decrease of the input iceberg trade cost, more firms have the ability to access foreign input and reduce the marginal cost of production. In contrast to the mechanism analyzed in the standard model theory, where input trade liberalization leads to the reallocation of inputs from the low-productive to high-productive firms, this research shows that, in the presence of input and output distortions, input trade liberalization may reallocate the factors to both high-productive and subsidized firms. In this research, I assume the productivity and distortions are independent. That is to say, the subsidy could be taken by both the inherently high-productive and low-productive firms. There is a lot of evidence in China that government subsidies are given to state-owned firms and some private firms which have a special

relationship with the government. For example, Bai et al. (2020a) argues that China's extraordinary economic growth comes from the special deals provided for favored private firms. In general, these favored private firms are big and highly productive. From the counterfactual analysis, we also can find that the level of the mass of operating firms in distorted cases is less than that in the efficient case. Furthermore, the elasticities of the mass of operating firms with respect to the percent changes in the input iceberg trade cost are more sensitive in the distorted case. That is to say, in this research, we get to this situation that: first, distortions that drive the usage of factors (labour, domestic and foreign inputs) away from their first-best allocation and decrease the level of aggregate TFP, as well as decrease the mass of operating firms; input trade liberalization leads to more tough import competition and more resources are allocated to the high-productive and highly subsidized firms. Compared to the efficient case, the resources may be more concentrated on the high-productive and highly subsidized firms in the distorted case with the constant endowment and fewer operating firms. In Bai et al. (2019)'s paper, the final goods trade liberalization substantially decrease the aggregate TFP. They decompose the TFP loss into misallocation effect induced by the output distortion and selection effect generated by the entry and selection, and the latter is way bigger than the former under the trade liberalization. They also show that the absolute value of the elasticity of TFP with respect to trade liberalization under distorted case are larger than that under efficient case. In terms of the elasticity, their findings are consistent with my results that the selection effect induced by the input trade liberalization is stronger under distorted case with distortions.

Figure 2.3: Gain from input trade liberalization



Note: open efficient denotes the case without any distortions in an open economy, open distorted means the case with calibrated distortions in an open economy, closed efficient means the case without any distortions in a closed economy, closed distorted means the case with calibrated distortions in a closed economy

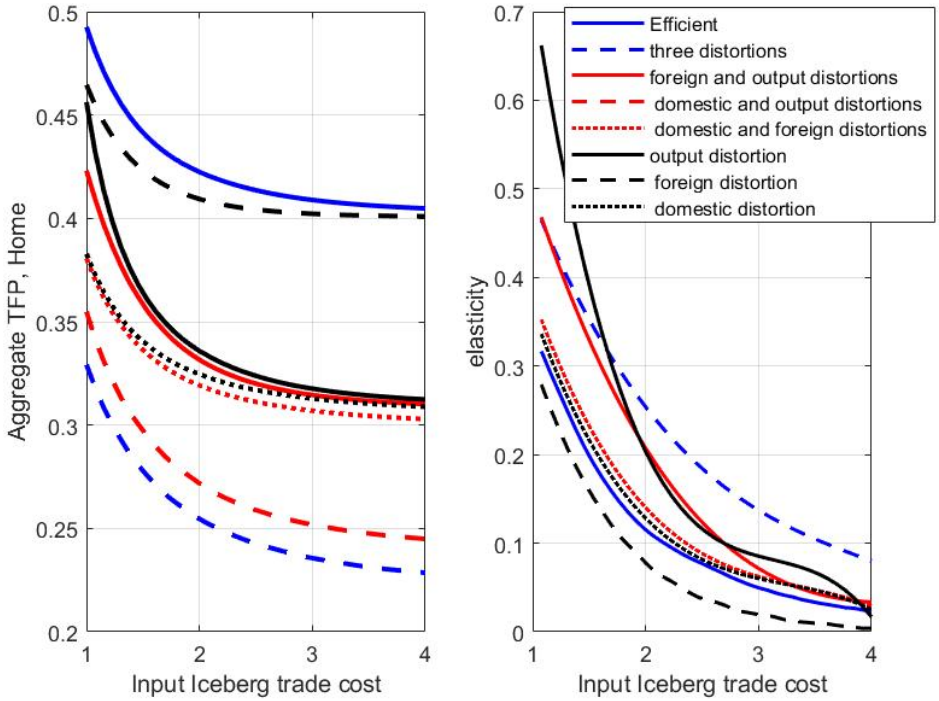
Table 2.3: Counterfactual analysis

	Panel (A): Autarky to open			
	aggregate TFP		mass of operating firms	
	(1) Efficeient	(2) Distorted	(3) Efficeient	(4) Distorted
percentage change in aggregate TFP	12.71%	17.71%	-7.97%	-11.66%
	Panel (B): Non-autrarky counterfactuals			
change in input iceberg trade cost by ...	(1) Efficeient	(2) Distorted	(3) Efficeient	(4) Distorted
... 5 percent	0.2%	0.63%	-0.114%	-0.194%
... 10 percent	0.44%	1.28%	-0.264%	-0.376%
... 20 percent	1.1%	3.11%	-0.624%	-0.886%

Table 2.4: Counterfactuals analysis with specific distortions

	(1)	(2)	(3)	(4)	(5)
change in input iceberg trade cost by ...	Efficient	Distorted with three distortions	Distorted with only domestic distortion	Distorted with only foreign distortion	Distorted with only output distortion
... 5 percent	0.2%	0.63%	0.22%	0.05%	0.29%
... 10 percent	0.44%	1.28%	0.48%	0.13%	0.66%
... 20 percent	1.1%	3.11%	1.36%	0.43%	1.91%
	aggregate TFP loss relative to efficient case				
Calibrated input iceberg trade cost		-47.9%	-23.6%	-1.3%	-22.6%

Figure 2.4: Gains from trade with different distortions



Note: (1) Efficient (efficient case without any distortions); (2) Three distortions (distorted case with output, domestic and foreign input distortions); (3) Foreign and output distortions (distorted case with foreign input and output distortions); (4) domestic and output distortions (distorted case with domestic input and output distortions); (5) domestic and foreign distortions (distorted case with domestic and foreign input distortions); (6) output distortion (distorted case with only output distortion); (7) foreign distortion (distorted case with only foreign input distortion); (8) domestic distortion (distorted case with only domestic input distortion)

2.7 Conclusion

Trade in intermediate inputs has become increasingly important in the world economy. This paper evaluates the aggregate TFP gains to input trade liberalization with firm-level output, domestic and foreign distortions. I build a two-country model which follows the preferences and entry in Melitz (2003) and combines Hsieh and Klenow (2009)'s definition of distortions on outputs and inputs and also includes imported intermediate input. I calibrate the distributions of the distortions rely on the distribution the import intensity.

We find that with other factors fixed, the aggregate TFP in the open economy is higher than that in the closed economy and the aggregate TFP of the efficient case is higher than that of the distorted case with calibrated distortions. Moreover, the aggregate TFP in both efficient case and distorted cases are increasing with the reduction of the input iceberg trade cost. Finally, the elasticity of aggregate TFP with respect to the input iceberg trade cost is higher under the distorted case than that in the efficient case, means that the input trade liberalization has a stronger selection effect under the distorted cases.

Chapter 3

Imported Robots and Exporting Performance

3.1 Introduction

China's unprecedented economic growth over the last four decades has established its status as the global hub of manufacturing. The country's access to the global market and integration of new technologies has been crucial factors in its economic success (Khandelwal et al. (2013); Brandt et al. (2017); Storesletten and Zilibotti (2014)). The classical growth theory always emphasizes the delay in imitating and adopting new technology in developing nations, resulting in a productivity gap across countries. China displays a distinctive viewpoint when it comes to embracing new technology, in contrast to other developing nations at the same developmental phase, particularly in terms of investment in the manufacturing sector. Industrial robots in China serve as an excellent illustration of this scenario. Recent years have seen an intense debate about industrial robots and their economic effects. Robots are becoming a more and more important inte-

gral part of the industrial production processes. Given the fact that China has the world's largest industrial robot installation which reached around 243,300 units in the year 2021, we have a strong incentive to investigate the effect of robot adoption on the Chinese economy.

Atkinson (2019) suggests that the next production system will benefit both developed and developing economies, though developing economies may gain less. Robot adoption will become a key driver of productivity growth and reshape global supply chains. My research takes a Chinese perspective and reveals an interesting finding: instead of reshoring production to higher wage nations, there is evidence of an increase in exports.

In this research, We construct a Chinese dataset including firm-level robots among Chinese manufacturing firms. We emphasise the manufacturing sector which accounts for over 80% of China's adoption of industrial robots. In fact, while China has seen a rapid increase in the usage of industrial robots, most of them are still imported from developed countries, particularly from Japan, South Korea and European countries. In the sample period from the year 2000 - 2013, We may take advantage of this fact. Cheng et al. (2019) shows that only about 5,800 robots were produced by Chinese domestic firms in 2012. This fact allows us to employ Chinese customs data to identify firm-level robot adoption in China.

We are not the first to link robot adoption and internation trade through the TFP and employment. However, most works of literature focus on how automation affects employment and wage in developed countries (for example, Graetz and Michaels (2018); Chiacchio et al. (2018); Borjas and Freeman (2019); Acemoglu and Restrepo (2020)). With the US industrial robot dataset, Acemoglu and Restrepo (2020) reports large and robust negative effects of robots on employment and wage across commuting zones.

Moreover, some researchers turn to investigate how automation in developed countries will not only affect their own labour market and trade but also that of their international trading partners from the perspective of developed countries (for example, Artuc et al. (2019); Faber (2020); Stapleton and Webb (2020); Wang (2021)). Wang (2021) reports a positive relationship between robot adoption and the labour supply of these robot-complementary workers, and the heterogeneous effects of robots on different types of workers, as well as an increase in the importing from developing countries. Few paper study the impact of robot adoption on firms' exports. Alguacil Marí et al. (2020) estimates the effect of robot adoption on the extensive and intensive margins of exports by employing the Spanish manufacturing firms' data. They define the extensive margin as the firms' probability of exporting, and the intensive margin as the export sales and the shares of exports in total output. They find that robot adoption has a positive and significant effect on firms' extensive and intensive margins driven by its positive effect on firm productivity. My paper conducts similar research but focuses on the effect on a different definition of extensive and intensive margins of exports.

In light of the above motivating facts, the main aim of this paper is to explore the effects of imported robot adoption on exporting performances in a more sophisticated way by applying an organised definition of dual margins. To do so, We merge the customs data collected by the Chinese General Administration of Customs (CGAS) with the Chinese manufacturing firms' data from the *Annual Survey of Industrial Firms* collected by the Chinese National Bureau of Statistics (NBS) and use the sample period from the year 2000 to 2013.

With this merged dataset, we can generate comprehensive information on the firm-year-product and the firm-year-destination level. So we

can identify the extensive margins as the number of exporting product-destination pairs, the number of exporting products, and the number of export destinations, as well as the intensive margins as the average value of each product-country pair, the average value of each exporting product, and the average value of each export destination. We also can use the merged data to identify the firm-level importing robots' information. We apply a combination of propensity score matching and difference-in-difference techniques to conduct the causal relationship between robot adoption and the extensive and intensive margins.

This research contribute to the robot and trade literature. From the results, we can see that the adoption of robots significantly increases the total exports of firms, which echoes some research (Acemoglu and Restrepo (2018); Artuc et al. (2019); Bernard et al. (2010); Alguacil Marí et al. (2020)). Artuc et al. (2019) analyze robots' impact on trade, wages, and welfare, and discovers a positive correlation between higher robot adoption and increased import-export activity due to reduced production costs. In addition, this research contribute the technology and multi-product trade literature. Using Chinese data, employing robots leads to a notable rise in firms' extensive margins. However, the impact on the intensive margins follows a different trend. Regarding the extensive margins, Alguacil Marí et al. (2020) finds that robot adoption increases firms' export probability; Bernard et al. (2010) discover that the heightened efficiency will enhance the range of products offered by the companies and enable them to set higher prices in both the local and global markets.

The rest of the paper is conducted as follows. Section 3.2 reviews the literature on robot and labour, robot and trade activity and dual margins. Section 3.3 presents the data and stylised facts. Section 3.4 describes the methodology applied. Section 3.5 shows the main results. Section 3.6

represents robustness tests. Section 3.7 represents further discussions. The last section concludes.

3.2 Literature review

This research complements a growing number of datasets that measure robot adoption at the firm level. The most widely used dataset on industrial robots is from IFR, which estimates the total number of robots delivered and installed from 1993 to 2021 at the country-industry and application level. Empirical papers have utilized this data source to construct measures of robot adoption and robot exposure at the level of country and industry (Artuc et al. (2019); Acemoglu and Restrepo (2020); Zhao et al. (2022); Du and Wei (2022)). In addition, more researchers have attempted to construct firm-level robot adoption data (Fan et al. (2021), China; Wang (2021), US; Alguacil Marí et al. (2020), Spain). I contribute to this literature by constructing a dataset that indicates firm-level robot adoption status for manufacturing firms in China.

3.2.1 Robots and labour market

The increasing use of automation raises concerns the new technology will distort the labour market (Akst (2013); Autor (2015)). Acemoglu and Restrepo (2018) build a conceptual framework that can help understand the implications of automation and the labour market. They apply the task-based approach, where automation is conceptualized as replacing labour in tasks that it used to perform. This type of replacement causes a direct displacement effect, reducing labour demand. If this displacement effect is not counterbalanced by other economic forces, it will reduce labour demand, wages, and employment. This model includes the fact that automation will reduce the costs of production and thus create a productivity effect, the induced capital accumulation, and the deepening of automa-

tion—technological advances that increase the productivity of machines in tasks that have already been automated. Among the empirical evidence, Acemoglu and Restrepo (2020) and Borjas and Freeman (2019) show that robot adoption may reduce employment and wages manufacturing sector using the US data. Aghion et al. (2019) applies the France data and finds a similar negative effect on employment at the zone industry level. With the 6 EU countries dataset, Chiacchio et al. (2018) impact for a set of European Union countries, finding that robots can directly displace workers from specific tasks and have a more significant displacement effect on workers of middle education and young age. The adoption of robots not only affects local firms in developed nations but also has the potential to decrease employment in offshoring countries by stimulating reshoring efforts. Faber (2020) uses Mexico as an example to show that US robots have a sizeable negative impact on employment. This displacement effect is stronger for men than for women, and strongest for low-educated machine operators. However, some examples also show that the effect of robots on employment is more complicated in the affected sectors. More specifically, Graetz and Michaels (2018) shows that increased robot adoption does not reduce total employment, although they displace low-skilled workers in specific tasks. Moreover, Antón Pérez et al. (2020) finds that the impact of robots on European labour markets in the last couple of decades has been small and ambiguous. Nevertheless, there is also evidence supporting that robots have a positive effect on employment with firm-level data(Dixon et al. (2020); Koch et al. (2021); Acemoglu et al. (2020); Bonfiglioli et al. (2020)). Regarding the findings for Chinese firms, Zhao et al. (2022) shows a significant positive correlation between robots adoption and employment in IT, health and service sectors, and the use of robots reduces labour demand in traditional industries such as mining and agriculture. Zhang et al. (2023), with micro-level data, finds that the adoption of industrial robots

increases firm-level employment in the manufacturing sector. Moreover, the effects of robots are mainly owing to the expansion of the output scale and increased productivity. Du and Wei (2022) shows that the massive adoption of robots is a significant driving force raising the unemployment rate while there is a reverse change in the longer period.

3.2.2 Robot and trade

We then proceed to an expanding literature on automation and trade. The findings regarding how automation technology affects trade have been discovered by certain researchers. Nevertheless, these studies predominantly concentrate on developed nations. Clearly, this could be attributed to the majority of industrial robots being deployed in OECD countries.

From the perspective of developed countries, the negative effect of automation on the labour market has prompted a debate on whether automation may serve as an alternative to offshoring and importing from developing countries (Wang (2021); Faber (2020); Bonfiglioli et al. (2020); Stapleton and Webb (2020); Artuc et al. (2019); Alguacil Marí et al. (2020); Stapleton (2020); Faia et al. (2021)). One of the important reasons why local firms in developed countries may decide not to offshore or even to reshore production processes domestically is that industrial robots significantly increase firms' productivity and reduce their production cost. More specifically, Bonfiglioli et al. (2020) uses a theoretical model to illustrate that, in the open economy with offshoring, automation lowers the relative wage of the workers that are displaced by the robots the most. That is to say, if robots displace foreign labour and domestic workers do not face any displacement effect. In this scenario, robots trigger reshoring. Empirically,

this paper, using trade data on US imports of industrial robots and intermediate inputs, finds that robots import tend to lower offshoring, both at industry and the commuting level. By conducting a similar analysis, Faber (2020) estimates the effects of US robots adoption on Mexico's labour market and results that US robots reduce employment in Mexico by reducing exports to the US. From the perspective of the developing countries, because of increased offshoring, many low-income economies such as Mexico, Colombia, India, and Vietnam have become more specialised in low-skill, manual tasks in the past few decades. These countries may lack the skills, capital, and infrastructure needed to participate in the global value chain and are particularly exposed to automation-induced international trade declines, as automation reshapes the relative labour cost which is the determinant of international competitiveness Rodrik (2018); Antras (2015); Artuc et al. (2019); Faber (2020); Kugler et al. (2020). In addition, researchers also pay attention to the effect of automation on exporting goods' quality. DeStefano and Timmis (2021) explore a new channel to estimate this effect in both developing and developed countries. They show that the widespread diffusion of robots employed to undertake a range of repetitive tasks that require a consistently high level of accuracy, in manufacturing production can lead to increases in the quality of exported products. China exhibits distinct characteristics in terms of the huge volume of industrial robot adoption when compared to other developing nations, wherein robots serve as a high-capital instrument in the context of investing. Lin et al. (2022) demonstrates that the utilization of industrial robots plays a crucial role in enhancing the quality of Chinese manufacturing export goods. Mechanism tests reveal the implementation of industrial robots contributes to the improvement of export product quality through enhanced labour productivity and increased human capital within enterprises.

3.2.3 Dual margins

Our research also contributes to the literature that investigates the sources of export growth: intensive and extensive margin. In traditional trade theories, products and firms are homogeneous, and the growth in exports is only related to an increase in export quantity and this is not decomposed into margins. Since the work of Melitz (2003), there has been an increase in the literature that decompose the firm's heterogeneity and export growth in foreign trade into intensive and extensive margins. The concepts of extensive and intensive margin are addressed as new trade relations (the number of exporting firms, the number of new trade partners) or a rise in existing trade relations (average exports per exporting firm) (Berke (2021)). Fernandes et al. (2018) using the World Bank's Exporter Dynamics Database featuring firm-level exports from 50 countries, and find that around 50 per cent of the variation in exports is along the extensive margin - a quantitative victory for the Melitz framework.

There is one paper which is mostly related to our research. Alguacil Marí et al. (2020) estimate the causal effect of robot adoption on the intensive and extensive margins of exporting using Spanish manufacturing firm-level data over the period 1994-2014. They apply the combination of propensity score matching (PSM) and difference in difference (DID) empirical tools and show that firms that start to use robots experience a sharp increase in their export probability, export sales and share of exports in total output, because of positive impact on firm total factor productivity (TFP) and import probability. Through these transmission channels, robot adoption firms might have more profit to pay export sunk costs and penetration costs and be more specialised in the production of intermediate inputs. Recent papers have found that China is different from other developing countries,

and the measured sophistication of China's export far exceeds what would be expected from its stage of development (Gao et al. (2014)).

Compared to previous literature, this paper contributes to exploring the effects of robots on exporting performances in a more sophisticated way by applying an organised definition of dual margins.

3.2.4 Background of Chinese robots

We focus on the adoption of industrial robots in China. According to ISO 8373:2021's definition, an industrial robot is an automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes.[1] This research emphasizes the manufacturing sector which accounts for over 80 per cent of China's industrial robots. According to the International Federation of Robots (IFR),[2] the World Robots 2022 Industrial Robots report shows a historical record of over 3.5 million industrial robots operating around the world and a high of half a million new industrial robots installed in 2021. China has the world's largest industrial robot installation which reached 243,300 units in 2021, a 44 percent increase from the year before. While China has been rapidly increasing the number of robots in operation in the country, many of those robots still come from foreign suppliers, particularly from Japan, South Korea, and Europe.'the rise of robots in China' shows that, in 2012, only about 5,800 robots were produced by Chinese local firms ((Cheng et al., 2019)). In 2020, foreign

[1]https://www.iso.org/standard/75539.html. For comparison, the ISO defines service robots as a robot that perform useful tasks for humans or equipment excluding industrial automation applications.

[2]The IFR Statistics Department collects statistical data on the annual installation of multipurpose industrial robots for around 40 countries. IFR also provides World Robots every year to show that global data on industrial robots in standardized tables and enables national comparisons to be made. Production, export, and import data are listed for selected countries. https://ifr.org/free-downloads/.

firms had a combined share of the Chinese market of 73 per cent, according to the IFR.

The incentives for robot adoption by Chinese firms are different from that located in developed countries. Rather than technological progress leading to an exogenous fall in robot prices, which promotes high-wage advanced economies to adopt robot, China's government policy (large subsidies and government-sponsored programs) play a prominent role in the development of industrial robots installation in China (Cheng et al. (2019)). The robots' installation offset China's rapidly ageing population and rising labour costs in the rapid transformation of the Chinese economy. The Ministry of Industry and Information Technology (MIIT) released its 'Guidance on the Promotion and Development of the Robot Industry' in 2013, which aimed for developing three to five world-class robot companies and reach a goal that the robot density of 10 per 1000 workers in factories. After this, a more well-known government program 'Made in China 2025' lists industrial robots and high-end computer numerical control (CNC) machines as one of the ten targeted sectors. Belton et al. (2020) address two goals of MIC 2025: first, China aims to increase its industrial robots density overall, increase its robots adoption in specific industries, and raise the quality of its locally manufactured robots and core components; second, China seeks to build at least three national champions and five regional hubs for robots manufacturing.

We then move on to those government policies that have been applied. Subsidies are by far the most prevalent. Yang (2017) shows that government subsidy schemes emphasize manufacturing, sales, and quantitative growth instead of research and development. Rather than focusing its resources on a few top projects, the central government delegated the tasks of robot subsidies to the local government. For example, at a regional level,

the government of Guangdong Province set up a USD 150 billion fund to encourage robot adoption and innovation. Sharif and Huang (2019) explains the 'Replacing Humans with Machines' initiative employed in Dongguan, Guangdong. They find that the subsidies awarded by the local government to encourage automation in the local firms played only a minor role in the firms' robot adoption decision. Instead, the key drivers of automation are rising minimum wage, new labour laws stipulating the responsibility of employers, increasing TFP, and improving product quality. Yang (2017) criticize these government policies and doubts the effect in the long run. In contrast, Artuc et al. (2019) address that China's robot subsidies now push them closer to the comparative advantage profile of developed countries and away from that of emerging economies.

3.3 The Data

We use the same matched dataset as in the second chapter. CGAS includes export and import flow from 2000 to 2013 at the HS eight-digit level. For each international transaction, the customs data records detailed information including firm identification information, import and export values, quantities, products, sources and destinations, and each commodity's HS code. We identify imports of industrial robots by each firm in the customs data using the commodity's HS6 code[3]. Both NBS databases and Customs dataset have their record of exporting values. We use firms' exporting information in the customs data to keep the trade values consistent with the number of exporting products and the number of export destinations. Moreover, we generate the number of varieties, the total export value for each exporting variety, the number of export destinations and the total export value for each country on a firm-year level. The International Federation of Robotics (IFR) has a database that provides information on the installation of industrial robots across various countries and industries, which is the new dataset used in this research. This database is frequently used in academic analyses (Acemoglu and Restrepo (2020), Faber (2020) and Borjas and Freeman (2019) for the US; Aghion et al. (2019) For France; Chiacchio et al. (2018) and Graetz and Michaels (2018) for EU countries). The IFR receives data from multiple sources for this database. Firstly, na-

[3]Industrial robots are counted under the HS6 code: 851531 (Fully or partly automatic machines for arc welding of metals, incl. plasma arc welding); 847950 (Industrial robots for multiple uses, Other industrial robots (excluding multi-functional industrial robots) and robots end-control devices), 851521 (Robot for resistance welding of metals, for automobile production line, Other resistance welding robot), 851580 (Robot for laser welding of metals, for automobile production line, Other kinds of welding machine and device), 842489 (Spraying robot), 842890 (Handling robot), 848640 (Automated material handling machines solely or principally of a kind used in the electronic integrated circuits factories); HS8 code: 84795010 (multi-functional industrial robot), 84795090 (other unlisted industrial robots), 84248920 (spraying robot), 84289040 (handling robot), 84864031 (automatic handling robot for integrated circuit factory), 85152120 (resistance welding robot), 85153120 (arc welding robot) and 85158010 (laser welding robot). https://www.transcustoms.com/

tional robotics associations collect data on their national robot markets and share it with the IFR. Secondly, almost all major industrial robot suppliers worldwide directly report their installation data to the IFR Statistical Department. In 2005, these suppliers provided consolidated data classified by country, industry, or application for the first time. Since 2010, the IFR has used the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 scheme for industry identification. Before 2010, data were categorized according to ISIC 2 or 3.

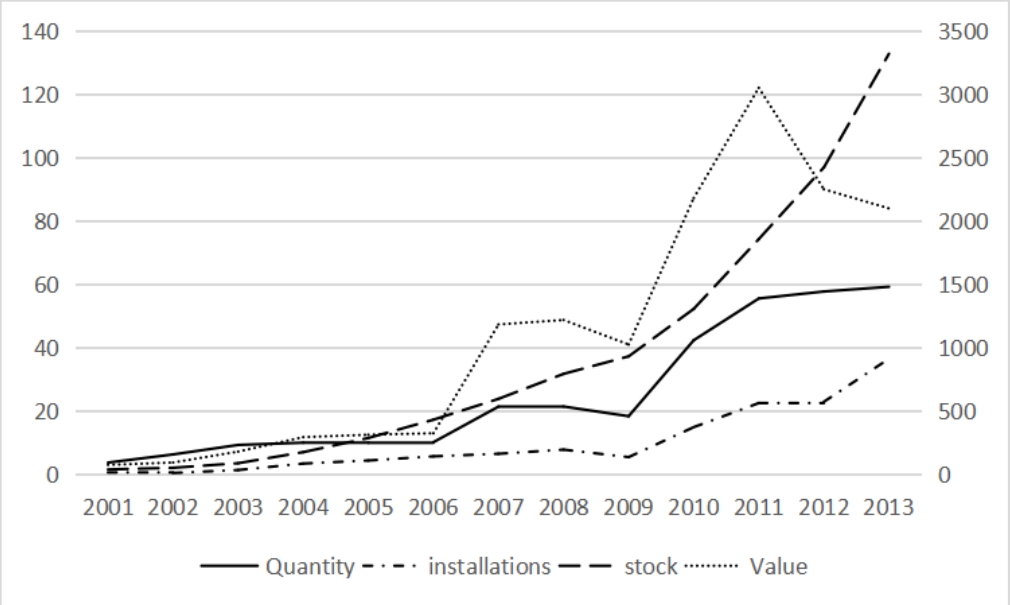
3.3.1 Stylized facts and main variables

Figure 3.1 plots the number of imported robots according to the Chinese customs database from 2000 to 2013. The quantity of import robots increased at a very high annual rate, from 2.65 thousand units in 2000 to 59.26 thousand in 2013. This figure also shows that the value of imported robots increased from 59.3 million US dollars to 2,100 million US dollars in the same period. Moreover, in this figure, the IFR data shows that the installation of robots in China has been increasing year by year, from 0.38 thousand units in 2000 to 36.6 thousand units in 2013. The growth trend and magnitude were almost the same for customs and IFR data. After 2013, the installation data from IFR began to exceed the number of imported robots by Chinese firms, explained by the increasing domestic robots production in China (Cheng et al., 2019). Such evidence explains why we use the data with the period from 2000 to 2013, and importing robots can be used as a proxy variable for robot adoption in China.

Figure 3.2 shows the share of robots across industries in the manufac-

turing sector in China using IFR data. The leaders in robot usage are the automotive and electronics industries, followed by plastic and chemical, industrial machinery, and metal products. Textiles, wood and furniture, paper production, and glass and ceramics are among the industries in which robot adoption is still rare. The higher rate of robot adoption in the automotive and electronics industries has implications for the future of robots in China. China has been the largest national producer of automobile units since 2008. China also clearly dominates the global electronics industry: over 70% of the world's computers and electronics are made in China.

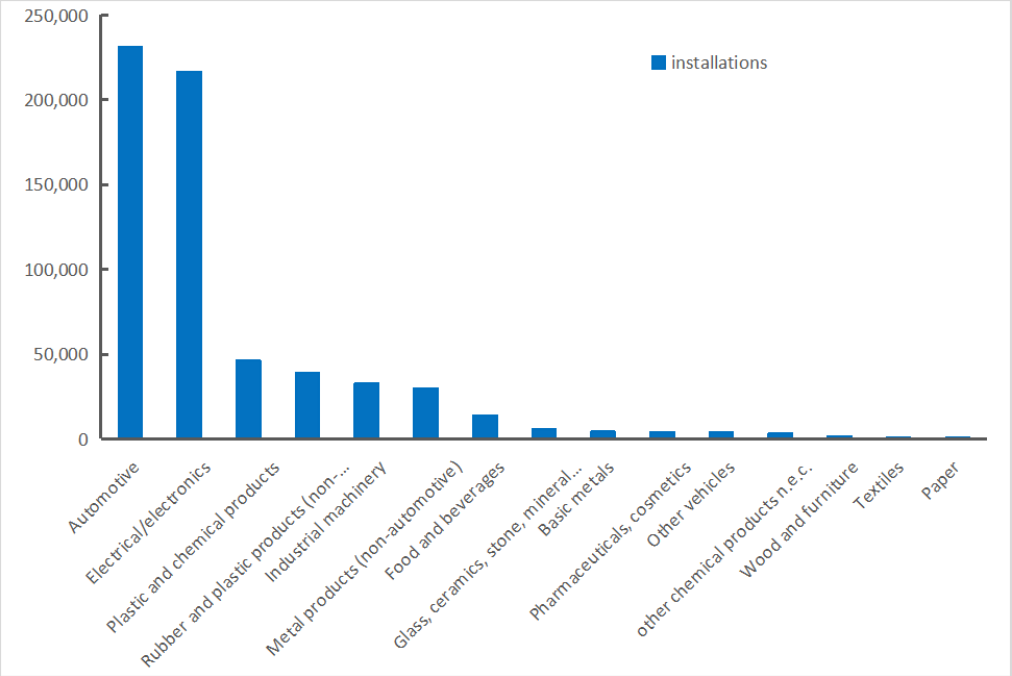
Figure 3.1: China's robot stocks from 2000 to 2013



Note: Data sources: IFR data and Customs data

Table 3.1: covers summary statistics for the main variables: Log labour, Log sales, fixed assets, Age, Log wage, total factor productivity (TFP), the count of exported product-destination pairs (Log No. Pair), the average value of each product-country pair (Log Av. Exp per pair), the number of exported product (Log No. Product), the average value of each exported product (Log Av. Exp per Product), the number of exported destination (Log No. Country) and the average value of each destination (Log Av. Exp

Figure 3.2: Industrial Composition of Robot installation in China



Note: Data sources: IFR data

per Country), and Robot dummy. Table 3 below summarizes the definition of all key variables.

Table 3.1: Summary statistics

Variable	Mean	Std.Dev	Min	Max	Obs
Log labour	5.402	1.114	2.079	12.32	655,957
Log sales	10.97	1.391	0	19.28	655,957
Log wage	2.869	0.826	-7.371	11.65	513,435
TFP (LP)	6.862	1.165	0.000129	13.92	313,024
Age	10.06	7.358	1	65	655,957
Log capital	9.223	1.75	0	19.08	655,957
Robot dummy	0.00751	0.0863	0	1	655,957
Log No.Pair	2.213	1.313	0	9.411	655,957
Log Av.Exp per pair	11.8	1.68	0	20.75	655,957
Log No.Product	1.295	1.026	0	7.224	655,957
Log Av.Exp per Product	12.72	1.93	0	21.64	655,957
Log No.Country	1.58	1.151	0	5.242	655,957
Log Av.Exp per Country	12.44	1.825	0	21.7	655,957

Note: Author's calculation based on data used. Sales, exports, and wage are in annual terms and in thousand yuan.

We further divide the firms into two categories: Robot adopters and Non-robot adopters. More specifically, the robot adopter covers two kinds of firms: new robot adopters and existing robot adopters. We cover all the above information in Table 3.2. New robot adopters are firms that start to use robots at least one year after they are included in the sample, the existing robot adopters are firms that already use robots when they are first entering into the sample, and the non-robot adopter is firms that never use robot during the whole sample period. For example, if a firm appears in the sample in 2005, starts importing in 2005, and stops importing after the year 2005, it is included in the existing robot adopter group. In this research, we are mainly interested in the firms' behaviours: export intensive and extensive margin when and after a firm starts to use the robot, so we compare the post-robot behaviours of new robot adopters and non-robot adopters in our subsequent analysis. We take advantage of the fact that most industrial robots used in China are produced abroad, and we can measure robot adoption through robot imports in the sample period. This fact allows us to identify firm-level robot adoption using the corresponding robot imports. Nevertheless, there are some concerns about using the customs database to measure robot adoption. First, firms may use locally produced robots that are not included in the customs data. Second, firms may purchase imported robots from international intermediaries. This would result in underestimating firms' robot adoption decisions.

From Table 3.2, Columns (1) and (3) show that robot adopters are significantly larger than non-adopters, and robot adopters tend to hire more employees and have more total sales on average, respectively. In addition, robot adopters also tend to pay higher wages on average and are more total factor productivity. The firm age of robot adopters is bigger, and have a higher capital-labour ratio on average. Finally, in terms of

the extensive and intensive margin, robot adopters also tend to have a higher value than non-robot adopters on average. Therefore, it is clear that the firm behaviour of robot adoption is associated with a premium in size, wage, productivity, and dual margins. We then move on to a more detailed subgroups comparison. Column (5) and column (7) show that the new robot adopters are significantly larger than the existing robot adopters in size, TFP, age, and dual margins, and have smaller values in age and capital-labour ratio. One reason that might explain these results is our restricted definition of existing robot adopters. We define that the existing robot adopters are firms that already use robots when they are first entering into the sample. This definition will include a lot of firms that are very small, and the importing robot behaviour is their first time entering the international trade market.

Table 3.2: Firm characteristics (Mean and Std.Dev) by robot adopter status

	By Robot Status				By Detailed Robot Status			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Robot Adopter		Non-Robot Adopter		New Robot Adopter		Existing Robot Adpoter	
	Mean and Std.Dev	Obs	Mean and Std.Dev	Obs	Mean and Std.Dev	Obs	Mean and Std.Dev	Obs
Log labour	6.493(1.281)	17,780	5.371(1.093)	638,177	6.535(1.258)	11,844	6.41(1.322)	5,936
Log sales	12.50(1.732)	17,780	10.92(1.356)	638,177	12.52(1.696)	11,844	12.44(1.8)	5,936
Log wage	3.399(0.895)	14,357	2.853(0.819)	499,078	3.36(0.866)	9,660	3.48(0.947)	4,697
TFP (LP)	7.927(1.401)	8,640	6.832(1.143)	304,384	7.949(1.363)	6,193	7.871(1.492)	2,447
Age	10.21(6.020)	17,780	10.05(7.392)	638,177	10.88(6.334)	11,844	8.887(5.087)	5,936
Log capital	395.2(3077)	17,780	160.5(4343)	638,178	352.5(3141)	11,844	480.3(2944)	5,936
Log No.Pair	2.752(1.383)	17,780	2.199(1.308)	638,179	2.862(1.388)	11,844	2.531(1.347)	5,936
Log Av.Exp per pair	12.79(2.169)	17,780	11.78(1.656)	638,180	12.95(2.077)	11,844	12.47(2.31)	5,936
Log No.Product	1.788(1.122)	17,780	1.281(1.020)	638,181	1.842(1.14)	11,844	1.68(1.077)	5,936
Log Av.Exp per Product	13.75(2.473)	17,780	12.69(11.905)	638,182	13.97(2.348)	11,844	13.32(2.654)	5,936
Log No.Country	1.926(1.171)	17,780	1.570(1.149)	638,183	2.018(1.167)	11,844	1.743(1.156)	5,936
Log Av.Exp per Country	13.61(2.316)	17,780	12.40(1.799)	638,184	13.79(2.22)	11,844	13.26(2.458)	5,936

Note: Author's calculation based on data used. Sales, exports, and wage are in annual terms and in thousand yuan.

Table 3.3: Definition of main variables

Variables	Definition
Extensive Margin	
Log No.Pair	log the number of exported product-destination pairs
Log No.Product	log of the Number of exported product
Log No.Country	log of the number of exported destination
Intensive margin	
Log Av.Exp per pair	log of the average value of each product-country pair
Log Av.Exp per Product	log of the average value of each exporting product
Log Av.Exp per Country	log of the average value of each destination
Robot decision	
New robot adopter	firms that start to use robots at least one year after they are included in the sample
Existing robot adopter	firms that already use robots when they are first to enter into the sample
Non-robot adopter	firms that never use robot during the whole sample period
Firm performance	
Log labour	log of total employment
Log sales	log of total sales
Log wage	log of average wage per employee
Log Capital	log of total fixed assets
TFP	TFP (Levine and Patrine)

3.4 The empirical methodology

3.4.1 OLS

The main research strategy is to explore the impact of firm-level robot adoption on dual margins. We start by identifying the dummy variable for robot adoption. $Robot_{it}$ represents the variable denoting industrial robots imported by firm i in year t. It takes a value of one if firm i imports a robot from abroad in a specific year t and zero otherwise. Panel data reveals that importing robots is a significant long-term investment for each firm. It is common for firms to not import robots every year once they enter the international market. Typically, a robot has an average service life of 12 years [4]. In this section, we use this specific robot dummy definition to represent robot adopters' importing decisions. The approach adheres to this given specification:

$$Y_{it} = \alpha + \beta Robot_{it} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \qquad (3.1)$$

where Y_{it} is the dependent variable for firm i in year t. The dependent variables include the count of exporting product-destination pairs (Log No. Pair), the average value of each pair of exporters (Log Av. Exp per pair), the number of exporting products (Log No. Product), the average value of each exporting product (Log Av. Exp per Product), the number of exporting destination (Log No. Country) and the average value of each destination (Log Av. Exp per Country). $Control_{it}$ means the role of other

[4] According to IFR, the average service life of an industrial is 12 years, with an immediate withdrawal from service afterward. This assumption was investigated in a UNECE/IFR pilot study, carried out in 2000 among some major robot companies.

firm characteristics, including labour, capital, average wage, firm age, and ownership. λ_t, λ_c, and λ_k mean the year, industry, and location fixed effects, respectively. Fixed effects are included to control for time, industry, and location-specific trends and characteristics. The year dummies capture common shocks to activities across all firms. Since industries are important identifiers of eligibility for robot adoption incentives, we control for the industry-fixed effect. We add the firm fixed effect in this specification to sweep away all that variation in our panel data explained by an individual firm. The estimated results of robot adoption and dual margin performance are presented in Table 3.4. Column (1)-(6): Robot adoption and firms' extensive and intensive margin relationship indicated a positive and significant coefficient for robot usage at the 1% level. Controlling for variables, positive and significant effects remain in the extensive margin (column (7)) - the number of product-country pairs. No significant changes are observed in the other two extensive margins: the number of varieties (column (9)) and the number of country-level exporting destinations (column (11). Additionally, the coefficients for the intensive margin - the average value of each pair (column (8)) and each product (column (10)) - are not significant. column (12) reveals a positive and significant coefficient for robot usage in the average exporting value per country.

Table 3.4: Robot effect on export (OLS)

	Product-Country pair		Product		Country		Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.045***	0.051**	0.028**	0.068***	0.023*	0.073***	0.026*	0.026	0.018	0.034	0.007	0.045*
	(0.0150)	(0.0230)	(0.0140)	(0.0250)	(0.0120)	(0.0240)	(0.0140)	(0.0220)	(0.0140)	(0.0240)	(0.0120)	(0.0240)
Log capital							0.077***	0.085***	0.041***	0.120***	0.063***	0.098***
							(0.0020)	(0.0030)	(0.0020)	(0.0030)	(0.0020)	(0.0030)
Log labour							0.168***	0.179***	0.097***	0.250***	0.132***	0.214***
							(0.0030)	(0.0040)	(0.0020)	(0.0050)	(0.0030)	(0.0040)
log age							0.443***	0.304***	0.254***	0.493***	0.357***	0.389***
							(0.0110)	(0.0140)	(0.0090)	(0.0170)	(0.0100)	(0.0150)
log age2							-0.098***	-0.085***	-0.052***	-0.131***	-0.081***	-0.103***
							(0.0030)	(0.0040)	(0.0030)	(0.0050)	(0.0030)	(0.0040)
Constant	1.688***	11.437***	1.033***	12.092***	1.120***	12.006***	-0.279***	9.509***	-0.082***	9.311***	-0.461***	9.690***
	(0.0080)	(0.0110)	(0.0060)	(0.0120)	(0.0070)	(0.0110)	(0.0250)	(0.0320)	(0.0200)	(0.0380)	(0.0220)	(0.0340)
YearFE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957
Firms	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.4.2 Empirical model: DID and PSM-DID

There may be a reverse causal relationship between robot adoption and a firm's dual margin, that is to say, the decision of using robots by a firm in production may have a self-selection effect. we estimate the causal relationship between robot adoption and firm-level exporting characteristics by using panel staggered difference-in-difference regression. Moreover, We follow the practice of Heckman et al. (1997), Fan et al. (2021) and Huang et al. (2022), and use the PSM-DID method to further identify this casual relationship. It further differentiates the outcome variable, effectively eliminating the common trend between the treated and control groups. Thus, using the PSM-DID empirical method in our research may help solve the concerns of sample selection bias and reverse causality.

The key variable of interest is robot adoption, as shown above, indicating whether the firm i use importing robots at time t. The specification in this section, $Robot_{it} \in \{0, 1\}$ is a dummy that takes on value 1 in the first year in which the firm imports industrial robots and in all subsequent periods, and is equal to 0 otherwise. The basic idea is to take robot adoption as a 'treatment', so its effects can be examined by the standard methods of average treatment effect on the treated (ATT). In our analysis, the treatment group is the new robot adopters, and the control group is the never-robot adopters. We can write the average expected effect as

$$E(Y^1_{it+s} - Y^0_{it+s}|Robot_{it} = 1) = E(Y^1_{it+s}|Robot_{it} = 1) - E(Y^0_{it+s}|Robot_{it} = 1) \tag{3.2}$$

We re-scale the time periods in such a way that a firm starts to use robots at period t and uses $s \geq 0$ to denote the years after a firm starts to import robots. The basic idea is that, based on the observational data,

the analysis is subject to a missing observations problem that no firm can be observed in the state of being a robot adopter and meanwhile being a non-adopter. We may only observe one state from the data.

In our analysis, the outcome is the exporting extensive and intensive margin at time $t+s$ following importing robots. We denote the outcome by Y^1 if a firm starts to import and Y^0 if it does not. The reality is that Y^0 is not available for robot importers after they use the robot. As to get unbiased estimates of the ATT, we need to construct a control group including never-robot adopters that are conceptually identical to new robot adopters had they not started to import robots. This is motivated by the fact that, if new robot adopters and never robot adopters are significantly different prior to the treatment, then the observed $E(Y^0_{it+s}|Robot_{it}=0)$ for never robot adopters is not an unbiased estimation of $E(Y^0_{it+s}|Robot_{it}=1)$ for the new robot adopters.

Specifically, we employ the propensity score matching approach to construct the control group that had similar observable firm-level characteristics X_{it-1} in period $t-1$ but which did not import robot in all sample period Girma et al. (2002); Dai and Yu (2013); Huang et al. (2022). Conceptional, the matching method demands a sufficiently large control group to ensure each firm in the treatment group can match at least one firm in the control group. To estimate the propensity score for each firm, the following probit model is employed to identify the probability of importing robots:

$$P(Robot_{it}=1)=\Phi(F(X_{it-1})) \tag{3.3}$$

where $P(Robot_{it}=1)$ denotes the predicted probability of using an imported robot at time t for a firm i, $\Phi(.)$ represents the cumulative density function (CDF) of a normal distribution, and X_{it-1} includes a series of firm

characteristics, use to estimate the probability, one year prior to the period that a firm start to use an imported robot. As suggested by the literature, productivity is an important characteristic, however, in our research productivity is not available overall period. So we only use productivity from 2000 to 2007. Other variables include firms size as measured by total employment, fixed capital, firm age, exporting extensive and intensive margin (product-country level, product level, and country level), and a set of control dummies, including ownership and time (Girma et al. (2002); Dai and Yu (2013);?;Huang et al. (2022)).

PSM method follows the nearest neighbour-based approach. That is to say, that individual is selected from the candidates whose propensity score is the nearest to the propensity score of the firm to be matched in the treatment group. If multiple subjects from the candidates in the control group have equally close propensity scores to the counterpart of the treatment group, one of those is selected at random. Practically, we apply PSM with replacement and 1:5 matching.

One important process is to discuss the propensity score match quality. Two conditions are important for the consistency of the matching estimator: (1) balance test; (2) and the propensity score should have considerable overlap, so a large proportion of the treatment group can be matched.

Once we have this counterfactual in hand we use a difference-in-difference method to assess the impact of robot adoption on the exporting extensive and intensive margin. This equation estimated takes the form:

$$Y_{it} = \alpha + \beta_s \sum_{s=0}^{1} Robot_{it+s} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \quad (3.4)$$

We control for firm, year, industry, and location fixed effects and es-

timate the contemporaneous and lagged (one year after first-time robot adoption) effects of using robots to export dual margins.

3.5 Results

3.5.1 Difference-in-difference

In this section, control group firms refer to non-robot adopters from the raw dataset. The treatment group firms, on the other hand, are defined as the new robot adopters. In table 3.5, we present the causal effects of robot adoption on a firm's dual margins. Our outcome variables are extensive and intensive margins. Columns (1)-(6) display the results without control variables, while considering firm and year effects. In columns (7)-(12), we include control variables along with firm and year-fixed effects. The estimated results indicate a significant increase in firms' extensive margins on average after adopting robots in production. Specifically, Columns (7), (9), and (11) demonstrate an average increase of 21.8%, 29.2%, and 10.4% in the treatment group firms' amount of product-country pairs, number of exported products, and set of export destinations, respectively, following robot adoption. However, there is no noteworthy effect of using robots on the average exporting value per pair. The estimates further reveal an average 11% decline in the average exporting value per product for robot adoption firms. In Column (12), it is evident that robot utilization leads to a significant 7.8% decrease in the average exporting value per country.

Table 3.5: Robot effect on export (DID)

	Product-Country pair		Product		Country		Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.264***	0.0100	0.319***	(0.0440)	0.141***	0.134***	0.218***	(0.0360)	0.292***	-0.110***	0.104***	0.078**
	(0.0210)	(0.0320)	(0.0200)	(0.0360)	(0.0180)	(0.0330)	(0.0200)	(0.0310)	(0.0190)	(0.0340)	(0.0170)	(0.0320)
Log capital							0.077***	0.085***	0.041***	0.120***	0.063***	0.098***
							(0.0020)	(0.0030)	(0.0020)	(0.0030)	(0.0020)	(0.0030)
Log labour							0.167***	0.179***	0.096***	0.251***	0.132***	0.214***
							(0.0030)	(0.0040)	(0.0020)	(0.0050)	(0.0030)	(0.0040)
log age							0.444***	0.303***	0.255***	0.492***	0.358***	0.389***
							(0.0110)	(0.0140)	(0.0090)	(0.0170)	(0.0100)	(0.0150)
log age2							-0.099***	-0.085***	-0.052***	-0.131***	-0.081***	-0.103***
							(0.0030)	(0.0040)	(0.0030)	(0.0050)	(0.0030)	(0.0040)
Constant	1.691***	11.438***	1.036***	12.093***	1.121***	12.007***	-0.272***	9.507***	-0.071***	9.307***	-0.457***	9.692***
	(0.0080)	(0.0110)	(0.0060)	(0.0120)	(0.0070)	(0.0110)	(0.0250)	(0.0320)	(0.0200)	(0.0380)	(0.0220)	(0.0340)
YearFE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957	655,957
Firms	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501	163,501

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.5.2 PSM-DID

As we described above in the empirical method section, PSM-DID will further help us to identify the causal relationship between using robots and dual margins.

We conduct the variable balance test to compare the differences between the treatment group (new robot adopters) and control group (matched non-robot adopters) and check the quality of matching. Table 3.6 provides the balance test results. We calculate the standard bias of the covariates between the treated and control groups before and after the matching. The results show that most of the standard biases of the covariates between two groups significantly decrease after matching, indicating that the matching method of our analysis is effective. Furthermore, according to the t-test, we also can find that the t-test after matching is not significant at 10% statistical level. It indicates that the matching results are reliable and there are no significant differences between the treatment group and the control group. Table 3.7 provides the number of new robot adopters and matched new robot adopters in the treatment group by year. This table shows that our matching has successfully matched over new robot adopters during all periods. All the results suggest that the matching results in our analysis are proper, and confirm that the estimated results of our PSM-DID model are effective.

Table 3.8 presents the PSM-DID outcomes. Generally, employing robots leads to a notable rise in firms' extensive margins. However, the impact on the intensive margins follows a different trend. The estimates indicate that, on average, robot adopters exhibit an 8.6% increase in the number of product-country pairs, a 14.6% increase in the number of exporting products, and a 3.9% increase in the number of exporting countries. There is no

significant alteration in the average exporting value per pair and per country. The average exporting value per product experiences an 8% decline among robot adopters. From the results, we can see that the adoption of robots significantly increases the total exports of firms, which echoes some research (Acemoglu and Restrepo (2018); Artuc et al. (2019); Bernard et al. (2010); Alguacil Marí et al. (2020)). Artuc et al. (2019) analyze robots' impact on trade, wages, and welfare, and discovers a positive correlation between higher robot adoption and increased import-export activity due to reduced production costs. Żukrowska (2021) found that the widespread adoption of artificial intelligence can expand trade volumes and mitigate the negative impact of the COVID-19 pandemic on trade, using EU data. Acemoglu and Restrepo (2018) and Alguacil Marí et al. (2020) confirm that robots and Al will increase output and export through enhance the firm level of productivity. Regarding the extensive margins, Alguacil Marí et al. (2020) finds that robot adoption increases firms' export probability; Bernard et al. (2010) discover that the heightened efficiency will enhance the range of products offered by the companies and enable them to set higher prices in both the local and global markets. Bernard et al. (2010) and Feenstra and Ma (2007) find that the higher productive firm has the incentive to expand its distribution network and sell to more destinations. Then we turn to the intensive margins, after the application of robots, multi-product firms, driven by the objective of enhancing productivity and maximizing profits, inevitably make adjustments to their export product range. They will reallocate the enterprise's factor resources among different types of products. Bernard et al. (2010) also discover that the emergence of new products will squeeze the market share of existing products and reduce their profitability. In my study, the adoption of robots greatly boosts total export value and diversity, with no significant impact on intensive margins.

Table 3.6: Balancing tests

	Unmatched	Mean		%reduct	t-test		V(T)/
Variable	Matched	Treated Control	%bias	bias	t	p $\succ$ $\|t\|$	V(C)
Log No. Pair	U	3.000 2.364	45.4		20.17		1.10*
	M	2.999 2.972	1.9	95.8	0.560	0.576	0.87*
Log Av. Exp per pair	U	12.90 12.04	44.5		22.280		1.71*
	M	12.90 12.86	2.2	95	0.670	0.501	1.51*
age	U	13.31 11.87	22.1		9.150		0.80*
	M	13.32 13.43	-1.8	91.8	-0.510	0.608	0.57*
Log labour	U	6.841 5.936	91.2		47.440		1.94*
	M	6.836 6.816	2.1	97.7	0.580	0.562	1.05
Log capital	U	11.60 9.633	114.8		50.700		1.07
	M	11.59 11.63	-2.1	98.2	-0.630	0.530	0.88*
Log sales	U	13.02 11.62	95.3		49.970		1.99*
	M	13.02 13.02	0.1	99.9	0.020	0.984	1.02
SOE	U	0.0608 0.0277	16.2		8.650		
	M	0.0609 0.0624	-0.8	95.3	-0.200	0.841	

Table 3.7: Matched firms

Year	No.new adoptor	No.matched
2001	62	62
2002	94	94
2003	95	95
2004	76	76
2005	127	127
2006	94	94
2007	199	199
2008	140	140
2009	101	101
2012	190	190
2013	161	160
All	1339	1338

Table 3.8: Robot effect on export (PSM-DID)

	Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.086***	-0.0170	0.149***	-0.080**	0.039**	0.0300
	(0.0210)	(0.0320)	(0.0200)	(0.0350)	(0.0180)	(0.0330)
Log capital	0.124***	0.156***	0.075***	0.206***	0.093***	0.187***
	(0.0100)	(0.0140)	(0.0090)	(0.0160)	(0.0080)	(0.0150)
Log labour	0.195***	0.194***	0.139***	0.250***	0.133***	0.255***
	(0.0110)	(0.0160)	(0.0090)	(0.0180)	(0.0090)	(0.0170)
log age	0.584***	0.397***	0.371***	0.610***	0.477***	0.504***
	(0.0400)	(0.0590)	(0.0330)	(0.0670)	(0.0340)	(0.0610)
log age2	-0.127***	-0.102***	-0.072***	-0.157***	-0.106***	-0.123***
	(0.0130)	(0.0190)	(0.0100)	(0.0220)	(0.0110)	(0.0190)
Constant	-1.036***	8.985***	-0.839***	8.788***	-0.801***	8.750***
	(0.1120)	(0.1610)	(0.0980)	(0.1830)	(0.0950)	(0.1690)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	73,742	73,742	73,742	73,742	73,742	73,742
Firms	37,792	37,792	37,792	37,792	37,792	37,792

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.6 Robustness tests

In this part, we explore potential alternate approaches for showcasing a set of robustness checks for our analyses. The core conclusion in our PSM-DID model shows that robot adoption can significantly increase a firm's extensive margins and have a negative effect on the intensive margins. To ensure the robustness of this conclusion, we further conduct some extra regressions.

3.6.1 The alternative definition of a new robot adopter

We use two distinct definitions for new robot adopters to ensure the robustness of our analysis. We define new robot adopters as firms that begin using robots at least two years (001) or three years (0001) after they enter the sample. This ensures that the robot adopters have a substantial presence in the dataset. The results for 001 and 0001 are presented in table 3.9 and table 3.10, respectively. Notably, the estimated outcomes for both new definitions align with the findings of our PSM -DID model, affirming the robustness of our results.

3.6.2 Alternative time periods

We also employ the database covering the period from 2000 to 2009 for an additional robustness check. Firstly, some firms lack certain variable data in 2010. Secondly, despite an increase in the imported quantity during that period, the value of imported robots declined starting in 2012. Thirdly, the Chinese robot market was predominantly influenced by imported robots from 2000-2009. The outcomes are presented in Table 3.11.

We observe significant positive effects on extensive margins (number of pairs and exporting products) but no significant effects on any intensive margins, mirroring our benchmark model. Thus, we can indeed confirm the robustness of our prior findings.

Table 3.9: The alternative definition of new robot adopter (001)

	Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.082***	-0.055*	0.167***	-0.141***	0.032	-0.005
	(0.023)	(0.033)	(0.022)	(0.037)	(0.020)	(0.035)
Log capital	0.122***	0.134***	0.072***	0.184***	0.090***	0.166***
	(0.011)	(0.014)	(0.010)	(0.017)	(0.009)	(0.015)
Log labour	0.209***	0.183***	0.144***	0.248***	0.146***	0.246***
	(0.012)	(0.017)	(0.010)	(0.020)	(0.010)	(0.018)
log age	0.565***	0.370***	0.340***	0.596***	0.474***	0.461***
	(0.044)	(0.060)	(0.035)	(0.070)	(0.037)	(0.062)
log age2	-0.125***	-0.094***	-0.066***	-0.153***	-0.107***	-0.112***
	(0.014)	(0.020)	(0.011)	(0.022)	(0.011)	(0.020)
Constant	-1.037***	9.327***	-0.785***	9.076***	-0.802***	9.093***
	(0.123)	(0.158)	(0.108)	(0.185)	(0.103)	(0.167)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	66,274	66,274	66,274	66,274	66,274	66,274
Firms	36,132	36,132	36,132	36,132	36,132	36,132

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.10: The alternative definition of new robot adopter (0001)

	Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.070***	-0.122***	0.174***	-0.226***	0.020	-0.072*
	(0.026)	(0.037)	(0.026)	(0.042)	(0.022)	(0.039)
Log capital	0.119***	0.139***	0.066***	0.191***	0.090***	0.167***
	(0.011)	(0.014)	(0.010)	(0.017)	(0.009)	(0.015)
Log labour	0.206***	0.183***	0.142***	0.247***	0.143***	0.246***
	(0.013)	(0.017)	(0.011)	(0.020)	(0.011)	(0.018)
log age	0.563***	0.363***	0.346***	0.581***	0.475***	0.451***
	(0.045)	(0.061)	(0.036)	(0.071)	(0.038)	(0.063)
log age2	-0.123***	-0.090***	-0.067***	-0.146***	-0.106***	-0.107***
	(0.014)	(0.020)	(0.011)	(0.023)	(0.011)	(0.020)
Constant	-0.985***	9.288***	-0.724***	9.027***	-0.781***	9.084***
	(0.124)	(0.162)	(0.111)	(0.189)	(0.105)	(0.169)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	64,254	64,254	64,254	64,254	64,254	64,254
Firms	35,791	35,791	35,791	35,791	35,791	35,791

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.11: Alternative time periods (2000-2009)

	Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it	0.060**	0.015	0.123***	-0.047	0.025	0.051
	(0.024)	(0.037)	(0.022)	(0.041)	(0.021)	(0.038)
Log capital	0.078***	0.102***	0.045***	0.135***	0.061***	0.118***
	(0.012)	(0.018)	(0.010)	(0.021)	(0.011)	(0.019)
Log labour	0.232***	0.284***	0.165***	0.351***	0.161***	0.355***
	(0.014)	(0.019)	(0.012)	(0.022)	(0.012)	(0.020)
log age	0.563***	0.374***	0.377***	0.561***	0.448***	0.489***
	(0.044)	(0.064)	(0.037)	(0.073)	(0.038)	(0.067)
log age2	-0.125***	-0.094***	-0.076***	-0.143***	-0.102***	-0.116***
	(0.014)	(0.020)	(0.011)	(0.022)	(0.012)	(0.020)
Constant	-0.702***	9.068***	-0.634***	9.000***	-0.579***	8.945***
	(0.132)	(0.197)	(0.114)	(0.225)	(0.117)	(0.206)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	54,695	54,695	54,695	54,695	54,695	54,695
Firms	28,890	28,890	28,890	28,890	28,890	28,890

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.7 Further analysis

3.7.1 Dynamic effect

We are also interested in the dynamic effect of importing robots. To more carefully estimate how firm-level export activities change both before and after using robots, I run a set of event study OLS regressions using the following specification (Wang (2021)):

$$Y_{it} = \alpha + \sum_{k=-4}^{k=4} \beta_k Robot_{it+k} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \quad (3.5)$$

where Y_{it} indicates whether a firm has adopted robots in year $t + k$. Through the lead-lag coefficients, β_k, we can find the dynamic response of the firm-level y_{it} to the robot adoption in the four years before and after using robots. We set year $t - 1$ as the base year, so all coefficient estimates for β_k should be explained relative to the year before adoption. We show the dynamic analysis in Figure 3.3. From the results, pre-robot adoption has no significant trend for dependent variables from zero. After robot adoption, extensive margins show significant non-zero trends, but no significant trends for intensive margins.

Then, we will present the difference-in-difference matching estimates of robot adoption effects on the firms in their first and second post-adoption years. Table 3.12 below presents the results. The estimates show that in the year of using robots, there is on average a 7.6% decline in the treatment group firms' exporting values, followed by a 1% increase in the exporting value and a significantly higher 9.8% increase in that. The above result indicates that robot adoption has a persistent effect on the robot adopters' exporting behaviour. More specifically, there is a persistent increase in the

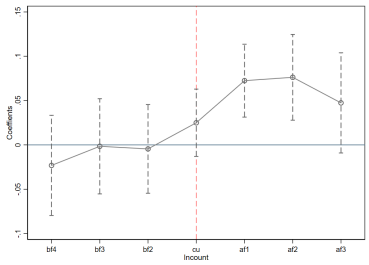
extensive margins. Column (1) indicates that, on average, robot adoption has a 1.3% increase (no significant) effect on the robot adopters' number of product-country pairs, followed by a significant increase of 7.3% in the numbers one year after adoption. Two years later, the number of pairs shows a significant increase of 11.3%. The results in columns (3) and (5) demonstrate a similar pattern. In terms of the effects on intensive margins, the results do not indicate a similar pattern compared to that on the extensive margins. Column (2) shows that using robot significantly decrease the average exporting value per pair in the year of adoption. There are no significant changes in the average value per pair in the first and second years after adoption. while column (4) indicates the most persistent decrease in three years and significant changes in the first two years, there are no significant changes in the robot adopters' average exporting value per country in all three years.

Table 3.12: Robot effect on export (dynamic effect)

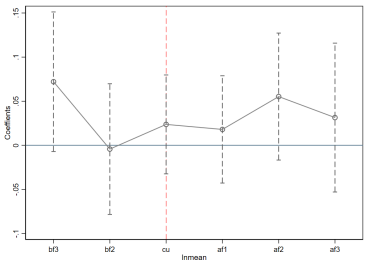
	Product-Country pair		Product		Country	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log No.Pair	Log Av.Exp per pair	Log No.Product	Log Av.Exp per Product	Log No.Country	Log Av.Exp per Country
Robot_it (shock year)	0.013	-0.089*	0.066**	-0.142***	-0.012	-0.064
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
one year later	0.073**	-0.064	0.115***	-0.106**	0.044	-0.035
	(0.04)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)
two year later	0.113***	-0.015	0.140***	-0.042	0.086**	0.011
	(0.04)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Log capital	0.112***	0.162***	0.0792***	0.195***	0.0807***	0.193***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Log labour	0.144***	0.168***	0.0959***	0.216***	0.0998***	0.213***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
log age	0.436***	0.04	0.297***	0.18	0.345***	0.13
	(0.07)	(0.10)	(0.06)	(0.11)	(0.06)	(0.10)
log age2	-0.0780***	(0.03)	-0.0477***	-0.0593**	-0.0595***	-0.0475*
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	-0.457***	9.648***	-0.475***	9.666***	-0.412***	9.603***
	(0.13)	(0.20)	(0.12)	(0.22)	(0.11)	(0.21)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	30,727	30,727	30,727	30,727	30,727	30,727
Firms	17,127	17,127	17,127	17,127	17,127	17,127

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

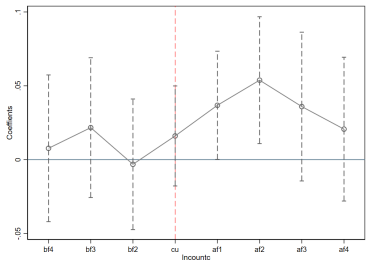
Figure 3.3: The parallel trend



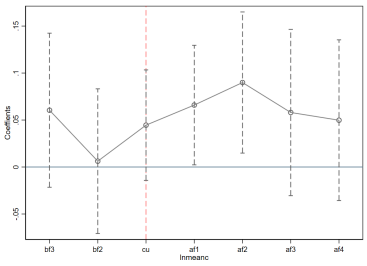
(a) Log No. Pair



(b) Log Av.Exp per Pair



(c) Log No. Country



(d) Log Av.Exp per Country

3.7.2 Impacting channels of robots in export

The results above demonstrate a notable and meaningful correlation between the adoption of robots and export. An inherent query that emerges is the nature of this correlation's mechanism.

If the robot boosts productivity, we foresee a favourable impact on TFP and price. This implies that firms can demand higher prices in the market due to improved efficiency and the introduction of new products. We use the Log price to show the average price in different dimensions. Columns (1)-(3) in Table 3.13 illustrate the empirical results of our mechanism analysis. The coefficient for the robots on TFP is 0.068 and is significant at the one per cent level. Robot adoption seems to promote exporting (extensive and intensive margins) through increased efficiency. Then we test the second possible mechanism. Column (4)-(6) in Table 3.13 illustrate the empirical results of our mechanism analysis that the coefficient for the robots on log price is 0.414 and is significant at the one per cent level. Furthermore, we observe that price exerts a substantial positive impact on extensive margins and a detrimental influence on intensive margins. Companies that implement robots can raise prices, increasing profits and expanding the range of products. They can also incur sunk costs by exporting to additional destinations, albeit at the expense of reducing the average export value of each product. This aligns with the findings presented in Bernard et al. (2010).

3.7.3 Capital intensity

The manufacturing industries are different in many dimensions, which have the potential to affect the firms' responses to robot adoption decisions. Ob-

Table 3.13: Channel test

	TFP			Price		
Variables	TFP(LP)	Log No.Pair	Log Av.Exp per pair	Log price	Log No.Pair	Log Av.Exp per pair
Robot_it	0.068***	0.100***	0.093**	0.414***	0.188***	-0.058*
	(0.0260)	(0.0250)	(0.0440)	(0.0520)	(0.0200)	(0.0310)
TFP(LP)		0.068***	0.140***			
		(0.0020)	(0.0040)			
Log price					0.072***	0.057***
					(0.0010)	(0.0020)
Log capital	0.014***	0.079***	0.070***	0.013***	0.076***	0.084***
	(0.0040)	(0.0030)	(0.0040)	(0.0030)	(0.0020)	(0.0030)
Log labour	0.345***	0.207***	0.220***	0.022***	0.166***	0.178***
	(0.0060)	(0.0050)	(0.0070)	(0.0050)	(0.0030)	(0.0040)
Log Age	0.495***	0.402***	0.271***	0.079***	0.438***	0.298***
	(0.0150)	(0.0150)	(0.0200)	(0.0170)	(0.0110)	(0.0140)
Log Age2	-0.113***	-0.095***	-0.073***	-0.012**	-0.098***	-0.084***
	(0.0040)	(0.0040)	(0.0050)	(0.0050)	(0.0030)	(0.0040)
Constant	4.140***	-0.854***	8.573***	1.466***	-0.377***	9.427***
	(0.0390)	(0.0380)	(0.0510)	(0.0370)	(0.0250)	(0.0320)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs	37,454	37,454	37,454	37,454	37,454	37,454
Firms	20,865	20,865	20,865	20,865	20,865	20,865

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

viously, the capital-labour ratio is a determinant of exporting and differs significantly across the manufacturing industries. We estimate if the main results of our analysis are sensitive to the capital-labour ratio of the manufacturing industries by running the regression using the intersection term between robot adoption and the capital-labour ratio. We calculate the capital-labour ratio of each 2-digit industry. The high capital-labour industries sub-group includes all industries with a capital-labour ratio higher than the 25th percentile of the total group. In contrast, the low capital-labour ratio industries sub-group are industries with a capital-labour ratio lower than the 75th percentile of the entire group. We present the result in the following table 3.14. We find that the effect on the intensive margins is stronger for firms from the high capital-labour ratio industries. In terms of the extensive margins, the results show no significant differences between firms from high-capital-labour and low-capital-labour industries. Based on the data, we see that industries characterized by a high capital-labour ra-

tio encompass major manufacturing sectors, namely the automobile, semiconductor, chemical, engine, and mining industries. Incorporating robots improves productivity and allows for higher pricing compared to industries such as the textile industry, furniture manufacturing, and sports and recreational equipment manufacturing.

3.7.4 Ownership

Following the definition of ownership in the NBS dataset, we classify the ownership structure into three groups: State-owned firms (SOEs); domestic private firms (DPFs), and foreign-invested firms (FIFs). The differences in the effect of robot adoption on all three ownership groups are always interesting when using Chinese data. Table 3.15 shows the results. The effects on foreign investment firms are the strongest, which may suggest that they have more capacity to utilize the robot and change their exporting performances.

3.7.5 Total factor productivity

The TFP may be the most important determinant of exporting performances and differs significantly across firms with each industry. From the table 3.16, we can find that the positive effect of robot adoption on the extensive and intensive margins is significantly larger along with the increase of the TFP. High TFP firms have a stronger ability to utilize the robots and more profits and experiences to enter the exporting market, and thus, their exporting activities are more sensitive to the robot adoption decisions. The above results are consistent with the findings in some research (Alguacil Marí et al. (2020); Acemoglu and Restrepo (2018); Artuc et al.

(2019); Bernard et al. (2010); Feenstra and Ma (2007)).

Table 3.14: Capital-labour ratio

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Product-Country pair		Product		Country	
	Log No. Pair	Log Av. Exp per pair	Log No. Product	Log Av. Exp per Product	Log No. Country	Log Av. Exp per Country
Robot_it*High K/L	0.072	0.196**	-0.008	0.276***	0.018	0.249***
	(0.064)	(0.086)	(0.058)	(0.100)	(0.065)	(0.092)
Robot_it	0.033	-0.184**	0.151***	-0.301***	0.037	-0.187**
	(0.059)	(0.076)	(0.053)	(0.089)	(0.062)	(0.081)
Log capital	0.126***	0.131***	0.079***	0.178***	0.092***	0.165***
	(0.014)	(0.022)	(0.012)	(0.025)	(0.012)	(0.023)
Log labour	0.186***	0.179***	0.132***	0.233***	0.127***	0.238***
	(0.016)	(0.024)	(0.013)	(0.028)	(0.013)	(0.025)
log age	0.575***	0.516***	0.337***	0.755***	0.517***	0.574***
	(0.057)	(0.089)	(0.045)	(0.104)	(0.049)	(0.090)
log age2	-0.117***	-0.128***	-0.056***	-0.189***	-0.113***	-0.132***
	(0.018)	(0.027)	(0.013)	(0.031)	(0.015)	(0.027)
Constant	-1.107***	9.192***	-0.893***	8.977***	-0.844***	8.928***
	(0.163)	(0.262)	(0.139)	(0.301)	(0.135)	(0.274)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Observations	37,454	37,454	37,454	37,454	37,454	37,454
Number of ss	20,865	20,865	20,865	20,865	20,865	20,865

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.15: Ownership

Variables	(1) Log No.Pair	(2) Log No.Pair	(3) Log No.Pair	(4) Log Av.Exp per pair	(5) Log Av.Exp per pair	(6) Log Av.Exp per pair	(7) Log No.Product	(8) Log No.Product	(9) Log No.Product	(10) Log Av.Exp per Product	(11) Log Av.Exp per Product	(12) Log Av.Exp per Product	(13) Log No.Country	(14) Log No.Country	(15) Log No.Country	(16) Log Av.Exp per Country	(17) Log Av.Exp per Country	(18) Log Av.Exp per Country
Robot it * SOEs	0.082			0.280**			0.049			0.313**			0.022			0.341***		
	(0.078)			(0.119)			(0.068)			(0.131)			(0.056)			(0.125)		
Robot it * FIFs		0.007			-0.135***			0.101***			-0.230***			-0.021			-0.107***	
		(0.024)			(0.036)			(0.021)			(0.039)			(0.022)			(0.038)	
Robot it * DPFs			0.034			-0.003			-0.088			0.118			0.095*			-0.064
			(0.067)			(0.081)			(0.059)			(0.088)			(0.052)			(0.086)
Robot it	0.081***	0.082***	0.083***	-0.034	0.070*	-0.017	0.146***	0.084***	0.156***	-0.099***	0.068	-0.090**	0.037**	0.053**	0.031*	0.009	0.099**	0.035
	(0.021)	(0.026)	(0.021)	(0.032)	(0.040)	(0.033)	(0.020)	(0.024)	(0.020)	(0.035)	(0.044)	(0.036)	(0.018)	(0.023)	(0.018)	(0.033)	(0.042)	(0.034)
Log capital	0.124***	0.124***	0.124***	0.156***	0.152***	0.157***	0.075***	0.078***	0.076***	0.205***	0.199***	0.205***	0.093***	0.093***	0.092***	0.186***	0.184***	0.188***
	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.009)	(0.009)	(0.009)	(0.016)	(0.016)	(0.016)	(0.008)	(0.008)	(0.008)	(0.015)	(0.015)	(0.015)
Log labour	0.195***	0.195***	0.195***	0.194***	0.196***	0.194***	0.139***	0.137***	0.138***	0.250***	0.254***	0.250***	0.133***	0.134***	0.134***	0.255***	0.257***	0.255***
	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)	(0.009)	(0.009)	(0.009)	(0.018)	(0.018)	(0.018)	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)	(0.017)
log age	0.585***	0.584***	0.584***	0.400***	0.397***	0.397***	0.371***	0.370***	0.371***	0.614***	0.611***	0.610***	0.477***	0.477***	0.477***	0.508***	0.504***	0.504***
	(0.040)	(0.040)	(0.040)	(0.059)	(0.059)	(0.059)	(0.033)	(0.033)	(0.033)	(0.067)	(0.067)	(0.067)	(0.034)	(0.034)	(0.034)	(0.061)	(0.061)	(0.061)
log age2	-0.127***	-0.127***	-0.127***	-0.102***	-0.101***	-0.102***	-0.072***	-0.073***	-0.072***	-0.157***	-0.155***	-0.157***	-0.106***	-0.106***	-0.106***	-0.123***	-0.122***	-0.123***
	(0.013)	(0.013)	(0.013)	(0.019)	(0.019)	(0.019)	(0.010)	(0.010)	(0.010)	(0.022)	(0.022)	(0.022)	(0.011)	(0.011)	(0.011)	(0.019)	(0.019)	(0.019)
Constant	-1.036***	-1.037***	-1.034***	8.988***	9.005***	8.985***	-0.838***	-0.853***	-0.845***	8.791***	8.821***	8.796***	-0.800***	-0.798***	-0.794***	8.753***	8.765***	8.745***
	(0.112)	(0.112)	(0.112)	(0.160)	(0.160)	(0.161)	(0.098)	(0.098)	(0.098)	(0.183)	(0.183)	(0.184)	(0.095)	(0.095)	(0.095)	(0.169)	(0.169)	(0.169)
Obs	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742	73,742
Firms	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792	37,792

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.16: Total factor productivity

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Log No. Pair	Log Av. Exp per Pair	Log No. Product	Log Av. Exp per Product	Log No. Country	Log Av. Exp per Country
Robot_it *TFP	0.039***	0.093***	0.052***	0.081***	0.024**	0.108***
	(0.013)	(0.022)	(0.012)	(0.025)	(0.011)	(0.023)
Robot_it	-0.242**	-0.694***	-0.296***	-0.640***	-0.151*	-0.785***
	(0.108)	(0.185)	(0.103)	(0.202)	(0.088)	(0.192)
log capital	0.083***	0.087***	0.057***	0.113***	0.057***	0.113***
	(0.015)	(0.023)	(0.013)	(0.026)	(0.013)	(0.024)
log labour	0.198***	0.286***	0.148***	0.336***	0.132***	0.352***
	(0.017)	(0.024)	(0.016)	(0.027)	(0.015)	(0.025)
Log Age	0.568***	0.543***	0.351***	0.760***	0.452***	0.659***
	(0.054)	(0.079)	(0.047)	(0.090)	(0.046)	(0.082)
Log Age^2	-0.130***	-0.130***	-0.074***	-0.186***	-0.107***	-0.153***
	(0.018)	(0.026)	(0.015)	(0.030)	(0.015)	(0.027)
Constant	-0.518***	9.065***	-0.606***	9.152***	-0.344**	8.890***
	(0.159)	(0.252)	(0.142)	(0.286)	(0.142)	(0.258)
YearFE	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y
Obs	38,075	38,075	38,075	38,075	38,075	38,075
Firms	21,113	21,113	21,113	21,113	21,113	21,113

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.8 Conclusion

This chapter investigates whether robot adoption has a causal implication on extensive and intensive margins of exports. The well-constructed dataset allows us to identify the causal effect: First, we can generate comprehensive information on the firm-year-product and the firm-year-destination level. So we can identify the extensive margins and the intensive margins of each exporter. Second, we also can use the merged data to identify the firm-level importing robots' information. Third, the abundant firm characteristic information allows us the conduct a high-quality propensity score matching.

Our research confirms that imported robot adoption plays a crucial role in firms' exporting performance. The main results indicate that using robots will significantly increase firms' export sales and extensive margins. This paper extends the current literature on robot adoption's effect on economic performance by adding a developing country's perspective. Further work can be done on evaluating how robot adoption will affect the firms' export probability to enrich the dual margin literature. This section examines if adopting robots has a causal impact on exporting's extensive and intensive dimensions. The dataset's solid construction enables the identification of the causal effect. Initially, we can gather comprehensive data on firm-year-product and firm-year-destination levels to determine the extensive and intensive margins for each exporter. Additionally, the merged data allows the identification of firm-level information on imported robots. Furthermore, the ample firm characteristic information facilitates high-quality propensity score matching.

Our study affirms that the adoption of imported robots plays a vital role in enhancing firms' exporting performance. The primary findings reveal that employing robots significantly boosts export sales and extensive mar-

gins for firms. By incorporating a developing country's perspective, this research expands the existing body of literature on the impact of robot adoption on economic performance. Future research could evaluate how robot adoption influences firms' export probability, enriching the literature on dual margins.

Chapter 4

Imported Robots and Innovation

4.1 Introduction

China's unexpected continuous economic growth has been the elephant in the room. Innovation and technological advancements have played crucial roles in driving this growth. Economic theories discussing the occurrence of middle-income traps, as observed in Latin American countries (Acemoglu et al. (2006)) focus on the failure of countries with weak institutions to guide a economic transition from the an investment-driven to an innovation-driven economic growth (Storesletten and Zilibotti (2014)). Will China face this situation in the near future? Notably, China is rapidly evolving into an innovation-oriented economy, far outpaces any other countries at a comparable development stage. Although a portion of China's success was historically attributed to its abundant supply of cheap manufacturing workers, the country has been facing the dual challenge of a shrinking labor force and significant increases in labor costs over the past decade (Li

et al. (2012)). The trend of declining population in China is difficult to improve in the short term.In that case, the trend of industrial production automation in the Chinese manufacturing sector is expected to accelerate to some extent. Given that China boasts the world's largest industrial robot installation, with approximately 243,300 units in the year 2021, and is the largest applicant in terms of patent filing, there is a compelling reason to explore the impact of robot adoption on innovation activities within China.

Similar to the impressive robot adoption statistics, China has also seen a drastic growth in patent applications received by the China National Intellectual Property Administration (CNIPA), even with a weak record of protecting intellectual property rights. Surprisingly, the total number of Chinese domestic patent filings increased from 8,558 in the year 1985 to 1.59 million in 2021, accounting for around half world's total applications. From 2011, China's patent office received the highest number of applications worldwide. Eberhardt et al. (2011) reports that a significant portion of Chinese entities' invention patent filing is belonging to the information and communication technology industry (ICT) from 1996 to 2006. From the Chinese robots installation data, we find the leaders in robot usage are the automotive and electrical and electronics industries. Another remarkable development is China's growing contribution to global research and development (R&D) which jumped from 2.2% in 2000 to 14.5% in 2011. An interesting question is how that robot adoption may affect innovation activities. while researchers always pay more attention to innovation in developed countries, this paper extends the literature on robot adoption's effect on innovation by adding the perspective of a country from the Global South.

To achieve this objective, we perform a dataset integration by combining the patent data obtained from the China National Intellectual Property

Administration (CNIPA) with the data on Chinese manufacturing firms from the Annual Survey of Industrial Firms, which is collected by the Chinese National Bureau of Statistics (NBS) and customs data. The dataset analysis covers the period from the year 2000 to 2013. With this merged dataset, we can identify the firm-year-level patent filings and the firm-level importing robots' information. In this research, we combine propensity score matching (PSM) with the difference-in-difference (DID) method to estimate the causal relationship between robot adoption and innovation activities.

We are not the first to link robot adoption and innovation activities. However, a large body of research on the influence of import robots focus on the service sector (Berezina et al. (2019); Blöcher and Alt (2021); Ivanov and Webster (2017); Kunz et al. (2019)). Wang (2021) examine the similar causal relationship using industry-level robot information. Gan et al. (2023) using a a sample of Chinese list manufacturing firms to examine the effect of robot adoption on green innovation. To the best of my knowledge, we study for the first time the impact of robot adoption on manufacturing firms' innovation, with NBS data and firm-level robot adoption information.

This research also contribute to import and innovation literature. A large body of research on the influence of imports focuses on firms' productivity (Goldberg et al. (2010); López and Yadav (2010); Halpern et al. (2015)). Chen et al. (2017) using Chinese data finds a positive and significant relationship between imports and firms' R&D intensity. Liu and Qiu (2016) argues that input tariff reduction may have heterogeneous effects on firms' patent filings: it may boost innovation because the cost of innovation activities decreases, but it may also reduce the firm's incentive to conduct innovation because of cheaper foreign technology. The implications of us-

ing imported industrial robots for the innovative capability and economic performance of manufacturing firms are still unclear. This study seeks to contribute to a better understanding of the causal relationship between using robots and the innovative activities of robot adopters. In this research, the innovation activities of firms as measured by patent filings.

The main results indicate that robot adoption will significantly increase firms' innovation activities (total patent and invention patent). More precisely, the estimates show that robot adoption on average increases by 5.3% in the total number of patents, 3.4% in the number of invention patents, 5.1% in the number of utility patents and 2.3% in the number of design patents. The high capital-labour ratio and the private firms have a stronger effect than others. This result is consistent with findings in Chen et al. (2017) that imports from high-income countries stimulate innovation through cost-reducing knowledge spillover. They also find that high-tech firms tend to experience a larger positive effect, as do private firms.

The rest of the paper is conducted as follows. Section 4.2 shows the literature review. Section 4.3 shows Institutional background of IPR regulation and the patent system in China. Section 4.4 presents the data and stylised facts. Section 4.5 describes the methodology applied. Section 4.6 shows the main results. Section 4.7 shows the robustness tests. Section 4.8 represents further discussions. The last section concludes.

4.2 Literature review

The innovation process is the result of a complex set of relationships among actors which are producing, distributing and applying various types of knowledge—tangible and intangible.

4.2.1 Policy environment and innovation

The innovation policies seek to establish an environment that fosters and enhances innovation activities (Aghion and Howitt (1990); Hall (2007)). In broad terms, innovation policies have traditionally emphasised the significance of safeguarding intellectual property rights (IPR), implementing tax programs, providing research and development subsidy policies, and regulating labour market policies. (Branstetter et al. (2006); Hall and Rosenberg (2010); Bloom et al. (2019); Garcia-Vega et al. (2021)). It is widely acknowledged in the literature that the intellectual property rights system holds significant influence over the advancement of innovation activities (Sweet and Maggio (2015); Papageorgiadis and Sharma (2016); Candelin-Palmqvist et al. (2012); Chen and Puttitanun (2005)). In terms of the enforcement fo the IPR itself, Papageorgiadis and Sharma (2016) examine the causal connection between the enforcement-related aspect of intellectual property rights (IPR) and innovation across a panel of 48 countries from 1998 to 2001. The findings reveal that higher levels of IPR enforcement strength within the specific country's IPR system have a notable and advantageous impact on national innovation. Under the premise of intellectual property rights regulation, Naghavi and Strozzi (2015) studies the interaction of emigration and IPR in determining innovation and find that IPR creates a stable policy environment to absorb potential gains and stim-

ulates domestic innovation activities using diasporas as sources of advanced knowledge. This paper focus on the situation of the Chinese economy, and the world has seen a gradual improvement in Chinese intellectual property right policy (Wechsler (2011); Frietsch and Wang (2007); Fang et al. (2017); Deng et al. (2019)). Fang et al. (2017) finds that IPR protection enhances Chinese firms' motivation to innovate and that private sectors are more responsive to IPR security than state-owned firms, which is a distinct feature of the Chinese economy.

Government research and development (R&D) subsidy policy is an additional policy aimed at stimulating innovation, grounded in robust theoretical reasoning. (Arrow (1972); Spence (1986)). Micro-empirical studies of the impacts of subsidies on firms' innovation are already voluminous and are growing fast in developed countries (Bérubé and Mohnen (2009) for Canada; Bronzini and Piselli (2016) for Italy; Jaffe and Le (2015) for New Zealand; Almus and Czarnitzki (2003) for Germany). Typically, these studies conducted with data from developed nations indicate that the acquisition of research and development grants has a substantial impact on the likelihood of manufacturing firms applying for patents. Additionally, the effects of such grants vary across firms of different sizes. In the realm of literature pertaining to Chinese studies, comparable findings can also be observed, albeit infused with distinct Chinese attributes (Wang et al. (2022); Chen and Zhang (2019); Wu et al. (2020); Fang et al. (2018)). Specifically, Wang et al. (2022) finds that political connection reduces the efficiency of government R&D subsidies to a greater extent when political uncertainty is high. In China, government plays a crucial role in supporting private sector innovation where a quarter of firms' R&D expenditure comes from government subsidies. Public grants provided by the government help alleviate capital constraints and address market failures in resource alloca-

tion. However, these grants may potentially introduce political distortions in firms' innovative activities. Fang et al. (2018) reveals that subsidies become significantly positively associated with future innovation after the anti-corruption campaign [1] and the Department of government innovation officials.

4.2.2 Robot and innovation

Robots and artificial intelligence reshape the nature of the innovation process and organisation of R&D (Cockburn et al. (2019)). In service sector, AI and robotics are perceived as key value drivers (Berezina et al. (2019); Blöcher and Alt (2021); Ivanov and Webster (2017); Kunz et al. (2019)) and experts expect the rise of these technologies to result in a wide-ranging disruption of traditional service operations and to inherit a large potential for process innovation (Bughin et al. (2018); Trantopoulos et al. (2017); vom Brocke et al. (2016)). Blöcher and Alt (2021) finds that the use of AI and robotics in restaurants revolutionize the guest experience and the management process of restaurant operations, which shows proposes a systematic identification of process innovation potentials. We then turn to research on the Chinese manufacturing sector, Wang (2021) examines the causal relationship between unconventional innovation and the adoption of robots through the lens of user innovation theory and finds that robots significantly increase firm innovation. In addition, they empirically analyse several mechanisms of robots as the source of innovation through the factor augmenting technology effect, displacement effect and absorptive capacity effect. Gan et al. (2023) using a sample of Chinese listed manufacturing

[1] This anti-corruption campaign is the largest organised anti-corruption effect in the history of the Communist in China since 2011. By the end of 2017, more than 280 senior government officials, 8,600 department-level officials, and 66,000 country-level officials had been investigated or arrested(Kong et al. (2020)).

companies over the time period 2011–2019, and find that the adoption of industrial robots positively affects green innovation. More specifically, the effect is stronger on firms facing more stringent environmental regulation, and firms owning high levels of investment in innovation activities, through labour cost saving and human capital structure adjustment.

4.2.3 Trade and Innovation

Generally speaking, globalization affects innovation through various channels: more competitive pressure, increasing market size, knowledge transfer, and foreign skill spillover. In particular, some studies using Chinese data uncover the causal relationship. Liu and Qiu (2016) uses Chinese firm-level data from 1998 to 2007, which captures a significant imported input tariff reduction in 2002 because of China's WTO accession, and reports that imported intermediate inputs tariff cuts reduce the innovative activities by Chinese local firms. They analyze two opposite effects on the innovation decision by firms. First, firms can purchase a larger quantity of imported inputs with more varieties and higher quality because of the reduction in the input tariff. This may hurt a firm's incentive to undertake innovative activities because the firm can increase its productivity and output quality by importing from foreign markets. Second, the embedded technology in the imported input may boost a firm's innovation by cutting the cost of R&D expenditure and increasing efficiency. In their research, the innovation-reduction effect dominants the innovation-booting effect in China. In contrast, Chen et al. (2017) constructs firm-level instruments for importing to investigate the relationship between imports and innovation and shows that the imported intermediates tend to increase importing firms' R&D intensity through cost-reducing knowledge spillover.

Moreover, they find that importing from high-income sources has a greater impact on innovation. In parallel to Chen et al. (2017)'s study, we analyze the causal effect on Chinese firms by using the particular imported inputs, imported industrial robots, which are mostly imported from developed countries from 2000 to 2013. Moreover, Lu and Ng (2012) estimate that a one-standard-deviation increase in a firm's import penetration ratio increases its likelihood of having engaged in an incremental innovation by 4.48 per cent using the Chinese firm-level data[2]. However, using China's World Trade Organization (WTO) accession as a quasi-natural experiment, Liu et al. (2021) finds that import competition reduces firm innovation.

[2]In Lu and Ng (2012) incremental innovations embody product innovations, new quality controls, new management practices, process innovation, and so on. Process innovations are small-step cost-cutting innovations

4.3 Institutional background of IPR regulation and the patent system in China

4.3.1 Intellectual property rights regulation in China

Before turning to the details of the patent system, we summarise the main features of the IPR regulation in China. In 1980, China joined the World Intellectual Property Organization (WIRO), marking the start of China's Modern IPR regulation. Domestic regulations included the Trademark Law in 1982, the Patent Law in 1984, and the Copyright Law in 1990 (Berrell and Wrathall (2003); Muehlfeld and Wang (2022)). Despite historically weak protection of intellectual property rights, China has made amendments to its patent law over the years, including revisions in 1992, 2000, and 2008. Certain amendments are in accordance with the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). These amendments guide the Chinese IPR regulation consistent with international standards. In practice, however, lots of evidence reveal that China generally has a poor record on IPR protection and significant variations exist across in their interpretation and enforcement of IPR law (Fang et al. (2017)). The public awareness of IPR protection in China is different from that in western countries. Bosworth and Yang (2000) observed that China possesses a rich heritage of Confucianism, wherein the acquisition of knowledge is believed to occur through emulation, emphasising the significance of imitation. Nevertheless, intellectual property rights (IPR) are implemented by the government to safeguard the original ideas of the intellectual property holder by prohibiting unrestricted replication. In regards to the enforcement of intellectual property rights (IPR), China adopts two distinct systems of enforcement: the judiciary approach and the adminis-

trative approach, each capable of addressing instances of IPR infringement. Nevertheless, enforcing both approaches poses challenges owing to inadequate infrastructure and mechanisms. (Frietsch and Wang (2007)).

4.3.2 Chinese patent system

In 1984, the Chinese government established the initial patent law, which came into effect on April 1, 1985, marking the start of modern Chinese patent history. Similar to the impressive adoption of robots, China has also witnessed a significant rise in patent applications received by the China National Intellectual Property Administration (CNIPA). Unlike European and American nations, China possesses three patent types, namely the invention patent, utility model patent, and design patent[3]. Invention patents pertain to any technical solution on products, methods, or the improvement to the product; utility model patents cover a new technical solution relating to the shape, structure or combination of a product; and design patents pertain to alterations in the shape and/or colour of a product. The criteria for acquiring each of these three patents differ significantly, with the invention application being the most demanding and the design application being the least demanding (Liu and Qiu (2016); Li (2012)).

According to the World Intellectual Property Organization (WIPO), the number of patent applications filed domestically in China has witnessed noteworthy growth, rising from 8,558 in 1985 to an impressive 1.59 million in 2021. This significant figure comprises roughly half of the total global patent filings recorded during that particular year. This number is more than twice the domestic filings in the United States. Additionally, China has surpassed the US as the leading country in international patent appli-

[3]https://www.epo.org/searching-for-patents/helpful-resources/asian/china/faq.html European patent office has a general information of Chinese patent system.

cations under the Patent Cooperation Treaty (PCT), with 68,720 filings.

Eberhardt et al. (2011) uses Chinese entities' invention patent filing from 1996 to 2006 and finds that a significant portion of the invention patent belongs to the information and communication technology industry (ICT). Prud'homme and Zhang (2019) demonstrates that patent filings in China are primarily concentrated in several areas in Eastern China (Guangdong, Beijing, Jiangsu, Zhejiang, and Shanghai). These regions are characterised by a higher number of entities and robust technological capabilities. Additionally, Liu and Qiu (2016) find that state-owned enterprises (SOE) dominated as the main inventors until the mid-1990s, while private firms assumed that role in subsequent years.

Many scholarly investigations have been conducted to explain the explosion of China's patent filings. Hu and Jefferson (2009) employed firm-level of large and medium-sized Chinese industrial enterprises to explore the factors which can explain the surge in China's patent filings. The study determined that the intensification of research, foreign direct investment, and amendments of the patent law can explain the patent explosion. Even though, we use patents as an indicator of innovation and technological knowledge recreation. Hu et al. (2017)' analysis suggests that non-innovation-related motives for acquiring patents may have played a significant role in the Chinese patent explosion recently, especially on the utility model patent application. Moreover, most of the growth of patent filings comes from firms that were not active in patent applications in the past. Finally, Eberhardt et al. (2016) and Long and Wang (2019) highlight that the Chinese government's policies promoting patent acquisition directly encourage the filing of patents.

Even though China is the top county in patent filings, patent quality

has not risen proportionately. According to He (2021), between 1985 and 2020, the utility and design patents granted in China account for 81-89 per cent of the total, and only 11-19 per cent are invention patents, which is the key indicator of the innovation quality of a country. The government's promoting policy (subsidy) has negative effects on average patent quality(Long and Wang (2019); Chen and Zhang (2019)). However, recently, Lin et al. (2021), based on Chinese provincial panel data from 1995 to 2010, find that the implementation of patent subsidy policy has a significant increase in patent quantity and quality. Since the implemented policies they study were designed to focus on subsidising expenses incurred during the patenting process, government plays a positive role in patent quality improvement.

Similar to the impressive robot adoption, China has also seen a drastic growth in patent applications received by the China National Intellectual Property Administration (CNIPA). Generally, China has a weak record of protecting intellectual property rights. China passed its first patent law in 1984, it has amended the patent a few times, including in 1992, 2000, and 2008. In addition, some of the amendments are related to the Agreement on Trade-Related Aspects of Intellectual Property Rights(TRIPS). Three are three types of patents: invention, utility model, and industrial design patent. According to World Intellectual Property Organization (WIPO), the total domestic patent filings increased from 8558 in 1985 to 1.59 million in 2021, or around half of the world's total patent applications in 2021[4]. This is more than twice the number of domestic filings in the US. Moreover, China also surpassed the US as the top country in international patent applications under the Patent Cooperation Treaty(PCT) and had 68,720 filings.

[4]http://www.gov.cn/xinwen/2021-03/03/content_5589856.htm

4.4 The data

Our empirical analysis uses three datasets: NBS data, customs data and CNIPA data. The CNIPA database contains detailed information on each patent since 1985 when CNIPA started to accept patent applications. The data includes patent information: application data, patent name, applicant's name, applicant's address, and the types of the patent (invention patent, utility model patent, industrial design patent). There are three types of patents: invention patent, utility patent and design patent. To examine the relationship between imported robots and innovation, we combine combine the CNIPA data to the merged dataset used in chapter 2. The match process follows the method used in Liu and Qiu (2016): we merge this two datasets using official names of firms, and then check the matched date with phone number and location.

4.4.1 Patent as innovation

We use the patent data of companies to reveal the economic effects of innovation linked to the adoption of imported robots. Based on various studies on innovation, patent filings (output of innovation) or R&D expenditures (innovation input) serve as the standard measurement. Each measure possesses advantages and disadvantages. Patent filings are regarded as a superior indicator of innovation since they encompass both visible and invisible innovation efforts and demonstrate the innovation's quality. The CNIPA data in our sample period provides comprehensive information on patent filings. Following these studies Hu and Jefferson (2009) and Liu and Qiu (2016), we employ patent filing as the measure of innovation in our research.

In addition, we need to mention the weaknesses of using patent. First, the weak protection of intellectual property right in China may hurt firms' incentive to apply for patents. Second, the Chinese government's patent subsidy policy may encourage firms to apply for patents and boost the number of patent filings, but the average quality is not comparable to that of developed countries. Third, firms often protect their innovations by using methods other than patents to keep the industrial secrets and lead over main competitors (Liu and Qiu (2016); Frietsch and Wang (2007); Hall (2007); Yu (2018)).

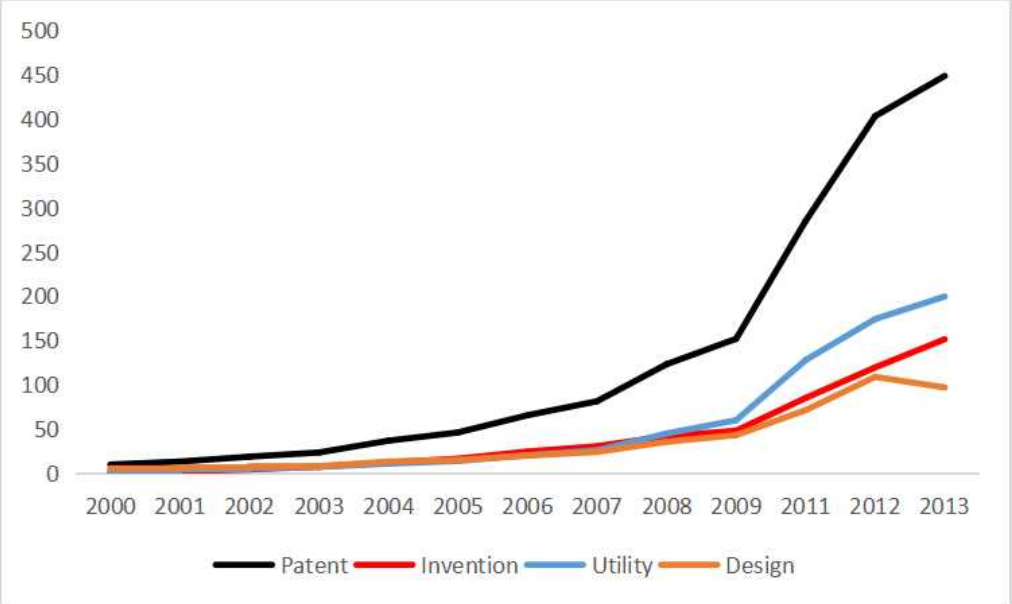
NBS data contains firm-level research and development (R&D) expenditure, which includes the direct expenditure on R&D activities, the indirect expenditure of management and services on R&D activities, the expenditure on capital construction and material processing by others, and conclude the expenditure on production activities, the fee paid to other entities on R&D activities (Chen et al. (2017)). Chen et al. (2017) argues that R&D is a representative indicator of innovation and that it measures the firms' independent innovation investment. They used NBS and customs data from 2000 to 2006 to conduct the analysis which shows that the import increased Chinese firms' innovation through promoting firms' R&D intensity. However, using R&D intensity also raises some concerns. Gorodnichenko et al. (2010) argues that adopting R&D expenditure as the proxy may be inappropriate because not all innovations are generated by R&D expenditure. Moreover, R&D expenditure, used as an input rather than output, does not necessarily result in innovation. They also show that R&D expenditures are less likely to be observed in emerging countries, China's lack of R&D data after 2006 reports the exact situation. Furthermore, the R&D measures are biased against small firms.

4.4.2 Stylized facts and main variables

Figure 4.1 plots the number of applications for several types of patents according to the CNIPA data. The number of total patent filings increased from 10,27 thousand to 448 thousand from 2000 to 2013. More specifically, the number of invention patents increase dramatically from 0.896 thousand to 151.41 thousand in the same period, as well as the application for utility and design patents show a similar pattern. Table 4.1 covers the summary of statistics for the main variable: the total number of patents (Log patent), the number of invention patents (Log Invention), the number of utility patents (Log Utility), the number of design patents (Log Design), fixed assets (Log capital), total employment (Log labour), total sales (Log sales), age, total productivity, and wage. I divide the entire group into several sub-groups and present the results in table 4.2. From this table, we can find that the state-owned firms (SOE) significantly have more patent filings than the non-SOE firms, and the firms in coastal provinces apply for more patents in all three types than inland firms, as well as firms in the High-tech industries, tend to own more patent filings than the firms in the low-tech industries.

Table 4.3 shows the definition of the main variables used in the analysis.

Figure 4.1: China's patent filing from 2000 to 2013



Data sources: CNIPA data.

Table 4.1: Summary Stastics

Variable	Mean	Std.Dev.	Min	Max	Obs
Log Patent	0.0970	0.461	0	9.700	3,446,736
Log Invention	0.0389	0.264	0	8.849	3,446,736
Log Utility	0.0612	0.345	0	9.116	3,446,736
Log Design	0.0253	0.239	0	7.077	3,446,736
Robot dummy	0.00160	0.0399	0	1	3,446,736
Log capital	8.712	1.779	0	19.34	3,446,736
Log labour	4.890	1.106	2.08	12.32	3,446,736
Log sales	10.43	1.442	0	19.98	3,446,736
Log wage	2.560	0.867	-7.371	13.51	2,678,347
TFP (LP)	6.469	1.184	0	14.99	1,784,250
Age	10.25	9.225	1	65	3,446,736

Note: Author's calculation based on data used. Sales, exports, and wage are in annual terms and in thousand yuan.

Table 4.2: Firm Characteristics (Mean and Std.Dev) by ownership, location and industry

Variable	SOE	Non_SOE	Coastal	Inland	High-tech	Low-tech
Log Patent	0.130 (0.549)	0.093(0.451)	0.104(0.478)	0.0817(0.418)	0.174(0.604)	0.057(0.361)
Log Invention	0.0651(0.365)	0.036(0.252)	0.0407(0.271)	0.034(0.248)	0.0752(0.369)	0.02(1.188)
Log Utility	0.086(0.429)	0.058(0.335)	0.0652(0.354)	0.052(0.322)	0.117(0.471)	0.032(0.252)
Log Design	0.024(0.231)	0.025(0.24)	0.028(0.257)	0.017(0.191)	0.036(0.273)	0.019(0.219)
Log capital	9.757(2.326)	8.612(1.684)	8.595(1.755)	8.98(1.802)	8.683(1.793)	8.726(1.771)
Log labour	5.348(1.409)	4.846(1.062)	4.858(1.099)	4.964(1.118)	4.844(1.131)	4.913(1.092)
Log sales	10.21(2.269)	10.46(1.335)	10.45(1.380)	10.4(1.577)	10.48(1.461)	10.41(1.432)
Log wage	2.516(1.146)	2.565(0.831)	2.617(0.814)	2.433(0.963)	2.673(0.861)	2.505(0.865)
TFP (LP)	6.08(1.693)	6.523(1.084)	6.496(1.124)	6.406(1.311)	6.551(1.197)	6.428(1.175)
Age	21.68(15.9)	9.159(7.453)	9.802(8.243)	11.27(11.09)	10.66(9.547)	10.03(9.049)

Note: Author's calculation based on data used. Sales, exports, and wage are in annual terms and in thousand yuan.

Table 4.3: Definition of main variables

Variables	Definition
Log Patent	log of the total number of patents
Log Invention	log of the number of invention patents
Log Utility	log of the number of utility patents
Log Design	log of the number of design patents
Robot decision	
New robot adopter	firms that start to use robot at least one year after they are included in the sample
Existing robot adopter	firms that already use robot when they are first enter into the sample
Non-robot adopter	firms that never use robot during the whole sample period
Firm performance	
Log labour	log of total employment
Log sales	log of total sales
Log wage	log of average wage per employee
Log Capital	log of total fixed assets
TFP	TFP (Levine and Patrine)

4.5 The empirical methodology

4.5.1 OLS

The main research strategy is to explore the impact of firm-level robot adoption on patents. We start by identifying the dummy variable for robot adoption. The strategy follows this specification:

$$Y_{it} = \alpha + \beta Robot_{it} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \qquad (4.1)$$

Where Y_{it} is the dependant variables for firm i in year t. The dependent variables include the total number of patents (Log Patent), the number of invention patents (Log Invention), the number of utility patents (Log Utility), and the number of design patents (Log Design). $Robot_{it}$ is a time-variant dummy variable. $Robot_{it}$ equals one when firm i imports robots in year t and zero for other circumstances. $Control_{it}$ means the role of other firm characteristics, including labour, capital, and firm age. λ_t, λ_c, and λ_k mean the year, industry, and location fixed effects, respectively. Fixed effects are included to control for time, industry, and location-specific trends and characteristics. The year dummies capture common shocks to activities across all firms. Since industries are important identifiers of eligibility for robot adoption incentives, we control for the industry-fixed effect. We use the firm-fixed effect in this strategy to control the variations explained by individual firms. The coefficient β thus captures the effect of robot adopters in dependent variables Y_{it}. Following Liu and Qiu (2016)'s method, we construct and use the following transformed measure as the dependent variable $Y_{it} = ln\left[(1 + y_{it}^2)^{1/2}\right]$ where y_{it} is the number of patent filings(total patent, innovation patent, utility patent, and design patent) by firm i in year t to avoid the problem of too many zeros values. After this

transformation, we can interpret the coefficient β as the percent change in the patent filing.

The estimated results of robot adoption and innovation of firms are presented in Table 4.4. With control variables, year fixed effect and firm fixed effect, columns (5)-(8) show that the coefficient of adopting robots is positive and significant for the firm's innovation activities.

Table 4.4: Robot effect on innovation (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Log Patent	Log Invention	Log Utility	Log Design	Log Patent	Log Invention	Log Utility	Log Design
Robot it	0.314***	0.235***	0.237***	0.059***	0.312***	0.234***	0.236***	0.058***
	(0.007)	(0.004)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)	(0.004)
lnk					0.023***	0.011***	0.016***	0.006***
					(0.000)	(0.000)	(0.000)	(0.000)
lnl					0.005***	-0.001***	0.002***	0.003***
					(0.000)	(0.000)	(0.000)	(0.000)
lnage					-0.040***	-0.025***	-0.029***	-0.007***
					(0.001)	(0.001)	(0.001)	(0.001)
lnage2					0.007***	0.005***	0.005***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.002	-0.013***	-0.007***	0.009***	-0.178***	-0.077***	-0.115***	-0.052***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
YearFE	Y	Y	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	3,446,736	3,446,736	3,446,736	3,446,736	3,446,736	3,446,736	3,446,736	3,446,736
Firms	840,255	840,255	840,255	840,255	840,255	840,255	840,255	840,255

Note: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.5.2 PSM-DID

This analysis aims to assess the causal effect of robot adoption on firms' innovation activities. We estimate the causal relationship by using panel staggered difference-in-difference regression. Obviously, for observational data, the fundamental problem is the 'missing counterfactual' treatment groups. That is to say, how the innovation activities would have been changed for the robot adopters had they not been using robots is unobservable in the sample. We employ the PSM-DID technique to solve the biased estimation problem.

The key variable of interest is robot adoption to indicate whether the firm i uses robots at time t. The specification $Robot_{it}$ in this section differs from the above. $Robot_{it}$ is a time-variant dummy variable, and takes the value of 1 in the first year in which the firm adopts robots and in all subsequent periods, and takes the value of 0 otherwise. The basic idea is to take robot adoption as a 'treatment', so its effects can be examined by the standard methods of average treatment effect on the treated (ATT). In this analysis, the treatment group is the new robot adopters, and the control group is the never-robot adopters. Specifically, we employ the propensity score matching approach to construct the control group that had similar observable firm-level characteristics but did not adopt robots in all sample periods. We employ the logit model to calculate the probability of using robots and present as follows:

$$Pr(Robot_{it} = 1) = \Phi(F(X_{it-1})) \tag{4.2}$$

where $Pr(Robot_{it} = 1)$ indicates the predicted probability, $\Phi(.)$ represents the cumulative density function of a normal distribution, and X_{it-1} includes a series of firm characteristics one year before the period that

a firm i start to adopt robots. In this analysis, we employ patents, total labour, total fixed assets, firm age, the average wage per labour, total factor productivity, and a set of dummy variables (e.g. industry, ownership and year) to estimate the propensity score for each firm. We use the nearest-neighbour approach to select the candidates from the control group whose propensity score is the nearest to that of the firm to be matched in the treatment group. We employ PSM with replacement and 1:5 matching in practice.

It should be mentioned that selecting suitable matching covariates is important to the quality of the matching results. That is to say, the distribution of covariates should be similar for the treatment group (new robot adopters) and the control group (non-robot adopters). In doing so, we use a balance test to check the quality of matching. We present balance test results in Table 4.5 and show that the standardized bias (% bias) is negligible for all covariates in the matched sample and is reduced substantially compared with that of the unmatched sample. Moreover, according to the t-test, we also can find that the t-test after matching is not significant for matching covariates. It indicates that the matching results are reliable and there are no significant differences between the treatment group and the control group. Table 4.6 shows that our matching has successfully matched over new robot adopters over the period.

Once we have this counterfactual in hand we use a difference-in-difference method to assess the impact of robot adoption on the firm's innovation activity. Specifically, we propose the following specification for our DID estimation:

$$Y_{it} = \alpha + \beta Robot_{it} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \qquad (4.3)$$

where Y_{it} is the innovation activity of firm i in year t; $Robot_{it}$ is composed of two terms: $Treat_i$ and $Post_t$, the former is the dummy variable which equals to 1 if the firm adopts robots and zero otherwise, the latter is an indicator of the post robot adoption period, which is equal to one in the first year in which the firm imports industrial robots and in all subsequent periods, and is equal to 0 otherwise; Like in the previous section, we introduce firm fixed effects denoted by λ_i to control for the time-invariant firm-specific characteristics. We also include the year fixed effects λ_t, location fixed effects λ_c and industry fixed effects λ_k; and ϵ_{it} is the error term. We control for time-variant firm characteristics that may affect firms' innovation activities. We cluster the standard errors at the firm level.

Table 4.5: Variable balancing test

	Unmatched	Mean		%reduct		t-test		V(T)/
Variable	Matched	Treated	Control	%bias	bias	t	p $\succ$ $\lvert t\rvert$	V(C)
Log patent	U	0.88986	0.253	56.3		38.78	0.000	3.58*
	M	0.88041	0.875	0.5	99.1	0.140	0.890	1.01*
age	U	13.4555	11.4	29.8		12.560	0.000	0.67*
	M	13.448	13.39	0.9	97.1	0.250	0.805	0.46*
Log labor	U	6.7931	5.764	105.3		60.790	0.000	2.18*
	M	6.7864	6.751	3.6	96.6	1.030	0.305	1.05
Log capital	U	11.586	9.621	114.8		54.120	0.000	1.1
	M	11.579	11.62	-2.3	98	-0.710	0.481	0.81*
Log sales	U	13	11.65	94		54.520	0.000	2.21*
	M	12.992	12.98	1	98.9	0.280	0.779	1
SOE	U	0.06842	0.052	6.7		3.290	0.001	
	M	0.06851	0.062	2.6	61.2	0.820	0.414	

Table 4.6: Matched firms

Year	No. New Robot Adoptor	No. of Firms Matched
2001	583	583
2002	611	609
2003	591	589
2004	623	622
2005	762	762
2006	693	692
2007	696	695
2008	559	558
2009	558	557
2012	393	392
2013	182	182
All	6251	6241

4.6 Results

The aim of this research is to find the causal relationship between robot adoption and firms' innovation activities. Table 4.7 presents the regression base on our PSM-DID specification, with the control variable and year and firm fixed effects. All estimations indicate that robot adoption leads to a positive and significant increase in the innovation of firms. In terms of the effects of the control variables, we find that firms having larger capital, larger employment, and shorter history have more innovation activities. More precisely, column (1) shows that there is on average a 5.3% increase in the treatment group firms' total patent filings. Columns (2)-(4) show that there is on average a 3.4%, 5.1%, and 2.3% increase in the target firms' application of invention patents, utility patents, and design patents, respectively.

Table 4.7: Robot effect on innovation (PSM-DID)

	(1)	(2)	(3)	(4)
Variables	Log patent	Log invention	Log utility	Log design
Robot_it	0.053**	0.034*	0.051**	0.023*
	(0.025)	(0.020)	(0.021)	(0.013)
Log capital	0.140***	0.102***	0.106***	0.038***
	(0.012)	(0.009)	(0.010)	(0.006)
ln labour	0.048***	0.026**	0.033***	0.015**
	(0.013)	(0.011)	(0.011)	(0.007)
lnage	-0.003	-0.070*	-0.003	0.019
	(0.048)	(0.036)	(0.041)	(0.025)
lnage2	-0.008	0.010	-0.006	-0.011*
	(0.013)	(0.010)	(0.011)	(0.007)
Constant	-1.711***	-1.213***	-1.303***	-0.445***
	(0.129)	(0.101)	(0.111)	(0.069)
YearFE	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y
Obs	86,368	86,368	86,368	86,368
Firms	52,398	52,398	52,398	52,398

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.7 Robustness tests

The core conclusion in our PSM-DID model shows that robot adoption can significantly increase a firm's innovation activities. To ensure the robustness of this conclusion, we further conduct some extra regressions.

4.7.1 Firm-level productivity

As we all know, firms with different levels of productivity may have different abilities to conduct innovation activities. We divide the sample into two groups: the high TFP group includes all firms with a TFP higher than the median value of the entire sample, whereas the low TFP group includes firms with a TFP lower than the median value of the entire sample. In this robustness check, our core findings remain robust. From Table 4.8 we can find that the effects of robot adoption on both high TFP and low TFP groups are positive and significant.

4.7.2 Firm location

Innovation activities in China are not even across the regions (Fu (2008)). We divide the firm's location into two groups: coastal and inland regions according to the NBS data. The coastal region includes provinces: Beijing, Tianjin, Liaoning, Shandong, Hebei, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan. The other provinces are included in the inland group. We report the results in Table 4.9. We find that the effects of robot adoption are positive and significant on firms both in coastal and inland regions. That is to say, our core conclusion is robust.

Table 4.8: Firm-level productivity

	High TFP	Low TFP	High TFP	Low TFP	High TFP	Low TFP	High TFP	Low TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Log patent	Log patent	Log invention	Log invention	Log utility	Log utility	Log design	Log design
Robot_it	0.065***	0.067***	0.053***	0.043***	0.057***	0.066***	0.035**	0.011
	(0.025)	(0.023)	(0.018)	(0.014)	(0.020)	(0.018)	(0.015)	(0.014)
Log capital	0.128***	0.145***	0.104***	0.083***	0.097***	0.110***	0.038***	0.038***
	(0.010)	(0.010)	(0.008)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
Log labour	0.058***	0.038***	0.037***	0.017**	0.038***	0.028***	0.016**	0.011
	(0.012)	(0.013)	(0.009)	(0.008)	(0.010)	(0.010)	(0.007)	(0.008)
log age	0.075	-0.046	-0.032	-0.029	0.052	-0.038	0.046	-0.027
	(0.052)	(0.055)	(0.038)	(0.034)	(0.043)	(0.044)	(0.032)	(0.034)
log age2	-0.021	-0.003	0.005	-0.002	-0.016	0.005	-0.018**	0.001
	(0.013)	(0.015)	(0.009)	(0.009)	(0.010)	(0.012)	(0.008)	(0.009)
Constant	0.015	-0.029	0.014	0.000	0.001	-0.029	-0.003	-0.013
	(0.029)	(0.032)	(0.021)	(0.020)	(0.024)	(0.026)	(0.018)	(0.020)
YearFE	Y	Y	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y	Y	Y
Constant	-1.827***	-1.485***	-1.434***	-0.864***	-1.382***	-1.149***	-0.492***	-0.343***
	(0.124)	(0.113)	(0.092)	(0.070)	(0.103)	(0.090)	(0.077)	(0.069)
Obs	46,006	40,362	46,006	40,362	46,006	40,362	46,006	40,362
Firms	24,244	28,154	24,244	28,154	24,244	28,154	24,244	28,154

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.9: Firm location

	coastal	inland	coastal	inland	coastal	inland	coastal	inland
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Log patent	Log patent	Log invention	Log invention	Log utility	Log utility	Log design	Log design
Robot_it	0.037**	0.218***	0.021	0.250***	0.042***	0.183***	0.014	0.108***
	(0.018)	(0.071)	(0.013)	(0.054)	(0.015)	(0.059)	(0.011)	(0.041)
Log capital	0.160***	0.053***	0.114***	0.041***	0.119***	0.041***	0.048***	0.002
	(0.008)	(0.018)	(0.006)	(0.014)	(0.007)	(0.015)	(0.005)	(0.011)
Log labour	0.043***	0.056**	0.025***	0.025	0.032***	0.036*	0.006	0.051***
	(0.010)	(0.023)	(0.007)	(0.018)	(0.008)	(0.019)	(0.006)	(0.013)
log age	0.008	-0.044	-0.044	-0.175***	-0.017	0.025	0.022	0.014
	(0.045)	(0.080)	(0.032)	(0.061)	(0.036)	(0.067)	(0.028)	(0.046)
log age2	-0.008	-0.002	0.005	0.030**	-0.001	-0.013	-0.010	-0.014
	(0.012)	(0.019)	(0.008)	(0.014)	(0.010)	(0.016)	(0.007)	(0.011)
Constant	-1.876***	-0.921***	-1.332***	-0.555***	-1.394***	-0.752***	-0.496***	-0.329**
	(0.095)	(0.227)	(0.067)	(0.172)	(0.077)	(0.190)	(0.059)	(0.131)
YearFE	Y	Y	Y	Y	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	67,017	19,351	67,017	19,351	67,017	19,351	67,017	19,351
Firms	38,382	14,017	38,382	14,017	38,382	14,017	38,382	14,017

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

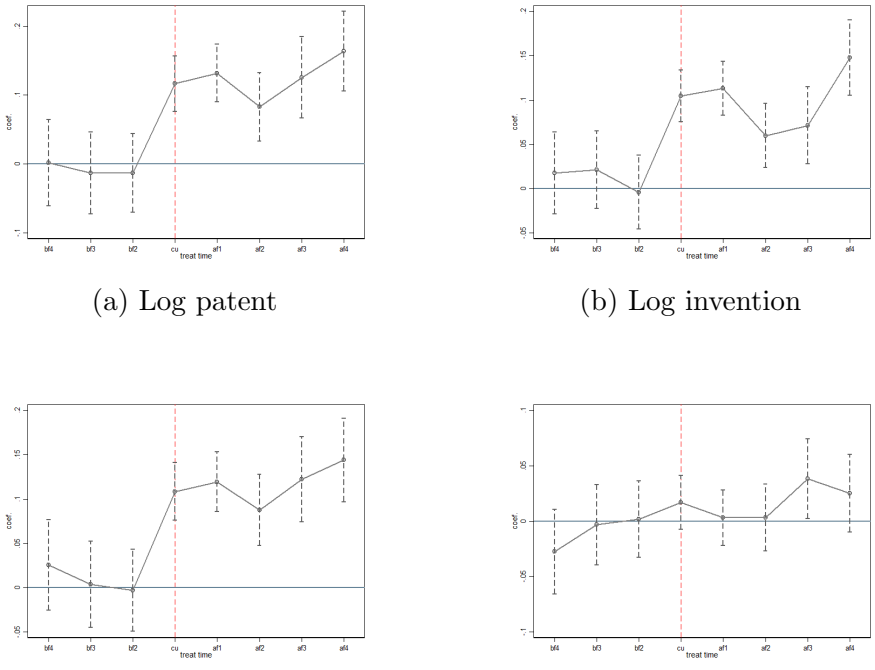
4.8 Further analysis

To more carefully estimate how firm-level innovation activities change both before and after using robots, I run a set of event study OLS regressions using the following specification (Wang (2021)):

$$Y_{it} = \alpha + \sum_{k=-4}^{k=4} \beta_k Robot_{it+k} + \gamma \sum Control_{it} + \lambda_i + \lambda_t + \lambda_c + \lambda_k + \epsilon_{it} \quad (4.4)$$

where Y_{it} indicates whether a firm has adopt robots in year $t + k$. Through the lead-lag coefficients, β_k, we can find the dynamic response of the firm-level y_{it} to the robot adoption in the four years before and after using robots. We set year $t-1$ as the base year, so all coefficient estimates for β_k should be explained relative to the year before adoption. We show the dynamic analysis in Figure 4.2. From the results, we can find that the pre-trends for total patents, invention patents, utility patents and design patents are not significant from zero, suggesting that there is no trend before robot adoption. The post-adoption trends for total patents, invention patents, and utility patents are significant from zero, though an increase in design patents only becomes significant after two years.

Figure 4.2: The parallel trend



(a) Log patent

(b) Log invention

(c) Log utility

(d) Log design

4.8.1 Impacting channels of robots in innovation

The results above demonstrate a notable and meaningful correlation between the adoption of robots and innovation activities. An inherent query that emerges is the nature of this correlation's mechanism.

If the robot boosts productivity, we foresee a favourable impact on TFP. This implies that firms can conduct more innovation activities due to improved efficiency. Columns (1)-(3) in Table 4.10 illustrate the empirical results of our mechanism analysis. The coefficient for the robots on TFP is 0.041 and is significant at the five per cent level. Robot adoption seems to promote innovation through increased efficiency (Stapleton and Webb (2020)); Dixon et al. (2020); Graetz and Michaels (2018). Next, we examine the second potential mechanism. Column (4)-(9) in Table 4.10 show the

empirical findings of our mechanism examination where the coefficient for robots on log wage and on log labour is 0.029 and 0.151, respectively, and is statistically significant at the 1% level. The firms that embrace robot implementation are motivated to increase their workforce and offer elevated wages due to a transformation in human capital structure that attracts a greater number of highly skilled workers. More employment and high-skill labour increase the firms' innovation activities. This aligns with the findings presented in research (Toner (2011); Evangelista and Savona (2003); Fassio et al. (2019); Bratti and Conti (2018)).

Then we turn to investigate how the firm characteristics affect the degree of the effect of robot adoption on firms' innovation activities.

Table 4.10: Channel test

	TFP			Logwage			Log labour		
Variables	(1) TFP	(2) Log patent	(3) Log invention	(4) Logwage	(5) Log patent	(6) Log invention	(7) Log labour	(8) Log patent	(9) Log invention
Robot_it	0.041*			0.029**			0.151***		
	(0.024)			(0.014)			(0.011)		
TFP		0.016**	0.007						
		(0.007)	(0.005)						
lnwage					0.120***	0.087***			
					(0.011)	(0.008)			
Log labour					0.111***	0.072***		0.039***	0.022**
					(0.012)	(0.009)		(0.013)	(0.009)
Observations	43,463	43,463	43,463	66,731	66,731	66,731	86,368	43,463	43,463
firms	27,450	27,450	27,450	42,948	42,948	42,948	52,398	27,450	27,450

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.8.2 Capital-labour ratio

From IFR data, we can find that the share of robot adoption is heterogeneous across industries in the manufacturing sector in China. The automotive and electronics industries are the leaders in robot usage. The capital-labour ratio is one of the key characteristics of firms and manufacturing industries. Moreover, capital intensity is a determinant of firms' innovation activity (Fu (2008)). In this analysis, we calculate the capital-labour ratio for each 2-digit industry. We define that the high capital-labour ratio group includes all industries with a capital-labour ratio higher than the 25th per-

centile of the total sample, whereas the low capital-labour group includes all industries with a capital-labour ratio lower than the 75th percentile of the total sample. We present the result in the following Table 4.11. From the table, we find that the average effect of robot adoption on high capital-labour ratio industry firms' innovation activities is significantly larger than that on the firms belonging to the low capital-labour ratio industry. This comparison is consistent with the fact that firms with a high capital-labour ratio conduct more innovation activities and are more affected by robot adoption.

Table 4.11: Capital-labour ratio

	(1)	(2)	(3)	(4)
Variables	Log patent	Log invention	Log utility	Log design
Robot_it* High K/L	0.084*	0.167***	0.069*	-0.085***
	(0.050)	(0.036)	(0.041)	(0.031)
Robot it	0.050***	0.029**	0.049***	0.026**
	(0.018)	(0.013)	(0.014)	(0.011)
Log capital	0.140***	0.102***	0.106***	0.038***
	(0.008)	(0.005)	(0.006)	(0.005)
Log labour	0.048***	0.026***	0.033***	0.015***
	(0.009)	(0.006)	(0.007)	(0.005)
log age	-0.004	-0.072***	-0.003	0.020
	(0.038)	(0.028)	(0.031)	(0.024)
log age2	-0.007	0.010	-0.005	-0.011*
	(0.010)	(0.007)	(0.008)	(0.006)
Constant	-1.710***	-1.212***	-1.303***	-0.446***
	(0.087)	(0.062)	(0.071)	(0.054)
YearFE	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y
Obs	86,368	86,368	86,368	86,368
Firms	52,398	52,398	52,398	52,398

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.8.3 Firm size

Firm size is a key factor to affect the firms' incentive to conduct innovation activities. In general, big firms may tend to have more high-skill workers and researchers to use robots and conduct research activities. Following Lu and Ng (2012)'s definition, the big-size sub-group includes firms with more than one thousand labour and more than 60 million US dollar in total sales. From Table 4.12, we can find that the effect of robot adoption on big-size firms is significantly larger than the effects on small-size firms. Generally, big-size firms have a stronger ability to absorb knowledge. Chen et al. (2017) show that how knowledge spillover affects the impact of imports on innovations is determined by the absorb ability.

4.8.4 Ownership

Following the definition of ownership in the NBS dataset, we classify the ownership structure into three groups: State-owned firms (SOEs); domestic private firms (DPFs), and foreign-invested firms (FIFs). Firms with different ownerships always show different ways of conducting innovation activities in China Liu and Qiu (2016). Table 4.13 indicates that the effects of robot adoption on SOEs and DPFs are positive and significant. However, the effect of using robots on foreign-invested firms is significantly negative. These heterogeneous effects are in line with the findings of Chen et al. (2017), that foreign firms don't appear motivated to innovate when they can do so in their home country. We expect that private firms are more innovative and will experience a greater innovation-enhancing effect from robot adoption and importing capital goods from developed countries.

Table 4.12: Firm size

	(1)	(2)	(3)	(4)
Variables	Log patent	Log invention	Log utility	Log design
Robot_it* Big Size	0.086***	0.121***	0.045**	0.017
	(0.023)	(0.017)	(0.019)	(0.014)
Robot it	0.021	-0.010	0.035**	0.017
	(0.019)	(0.014)	(0.016)	(0.012)
Log capital	0.140***	0.102***	0.105***	0.038***
	(0.008)	(0.005)	(0.006)	(0.005)
Log labour	0.041***	0.016**	0.029***	0.014**
	(0.009)	(0.006)	(0.007)	(0.006)
log age	0.002	-0.064**	-0.000	0.020
	(0.038)	(0.028)	(0.032)	(0.024)
log age2	-0.008	0.009	-0.006	-0.011*
	(0.010)	(0.007)	(0.008)	(0.006)
Constant	-1.670***	-1.155***	-1.282***	-0.438***
	(0.088)	(0.063)	(0.072)	(0.054)
YearFE	Y	Y	Y	Y
FirmFE	Y	Y	Y	Y
Obs	86,368	86,368	86,368	86,368
Firms	52,398	52,398	52,398	52,398

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.13: Ownership

	SOEs (1)	FIFs (2)	DPFs (3)
Variables	Log patent	Log patent	Log patent
Robot_it	0.425***	-0.192***	0.280***
	(0.045)	(0.019)	(0.042)
Log capital	0.143***	0.129***	0.104***
	(0.041)	(0.014)	(0.022)
Log labour	0.074*	0.021	0.089***
	(0.038)	(0.013)	(0.030)
log age	0.345**	0.129	-0.156
	(0.164)	(0.106)	(0.141)
log age2	-0.056*	-0.040	0.035
	(0.034)	(0.035)	(0.035)
Constant	-2.650***	-1.939***	-1.763***
	(0.556)	(0.311)	(0.404)
YearFE	Y	Y	Y
FirmFE	Y	Y	Y
Obs	5,906	23,956	28,180
Firms	3,166	13,357	23,267

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.9 Conclusion

This chapter investigates whether robot adoption has a causal implication on firms' innovation activities. We combine the NBS data, transaction-level customs data with the patents data. The well-constructed dataset allows us to identify the causal effect: First, we can identify the firm-level patent flings' information. Second, we also can use the merged data to identify the firm-level importing robots' information. Third, the abundant firm characteristic information allows us the conduct a high-quality propensity score matching.

Our research confirms that imported robot adoption plays a crucial role in firms' innovation activities. The main results indicate that using robots will significantly increase firms' applications for patents. The effect of using robots is larger on the high capital-labour ratio and the private firms.

This paper extends the current literature on robot adoption's effect on innovation activities by adding a developing country's perspective.In addition, we will have more accurate mechanism results if we have more information about the human capital structure in the data. This improvement can lead to better insights and a deeper understanding of the subject matter.

Chapter 5

Conclusions

China's economy is currently at a crucial turning point, facing a series of challenges and opportunities influenced by various domestic and international factors. The escalating trade war initiated by former U.S. President Trump in 2018, the accelerated restructuring of the global supply chain due to the pandemic, and the Biden administration's heavy blows to China's semiconductor manufacturing and telecommunication sectors have all posed significant threats to China's economic development. Additionally, the indefinite suspension of the China-EU trade agreement and China's differing stance from Europe on the Ukraine conflict have also greatly damaged trade and technological exchanges between China and Europe. Simultaneously, China is experiencing rapid aging and a continuous decline in birth rates, along with increasing labor costs compared to other developing countries, which will profoundly impact its economy.

However, there are also favorable aspects to China's economy. Being the world's largest trading nation, China's only choice is to persist with trade liberalization. China is also actively promoting the signing of regional trade agreements such as the RCEP. The expansion and continuous openness of

the Chinese domestic market will bring benefits to other countries. Moreover, China is deepening the market-oriented reform of state-owned enterprises and loosening the constraints of the household registration system, facilitating the free movement of people between urban and rural areas. The anti-corruption campaign has reduced special deals between local government and private sectors. All of these policies are likely to reduce the factor market resource misallocation.

The Chinese government has utilized industrial policies to provide subsidies to domestic enterprises engaged in the use and production of robots, thereby enhancing the level of automation in the manufacturing sector. This approach aims to address the challenges posed by a decreasing labor force and rising labor costs. Additionally, the government offers subsidies to innovative enterprises, while continuously strengthening the protection of intellectual property rights. Moreover, there is a growing alignment of public attitudes towards intellectual property rights with those of developed countries, which further encourages enterprises to increase investment in innovation. However, the role of industrial policies is unclear and may exacerbate resource misallocation in factor markets.

Overall, China should continue to reduce misallocation of resources in factor markets, promote trade liberalization, enhance the level of automation in manufacturing, improve its position in the global value chain, protect intellectual property, and encourage innovation. By doing so, the Chinese economy can achieve sustained growth.

Bibliography

Acemoglu, D., Aghion, P., and Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic association*, 4(1):37–74.

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with robots: Firm-level evidence from france. In *AEA Papers and Proceedings*, volume 110, pages 383–88.

Acemoglu, D. and Restrepo, P. (2018). Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda*, pages 197–236. University of Chicago Press.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Aghion, P., Antonin, C., and Bunel, S. (2019). Artificial intelligence, growth and employment: The role of policy. *Economie et Statistique/Economics and Statistics*, (510-511-512):150–164.

Aghion, P. and Howitt, P. (1990). A model of growth through creative destruction.

Ahn, J., Khandelwal, A. K., and Wei, S.-J. (2011). The role of intermediaries in facilitating trade. *Journal of International Economics*, 84(1):73–85.

Akst, D. (2013). What can we learn from past anxiety over automation? *The Wilson Quarterly*, 37(3):1–6.

Alguacil Marí, M. T., Lo Turco, A., and Martínez-Zarzoso, I. (2020). What is so special about robots and trade? Technical report, cege Discussion Papers.

Almus, M. and Czarnitzki, D. (2003). The effects of public r&d subsidies on firms' innovation activities: the case of eastern germany. *Journal of Business & Economic Statistics*, 21(2):226–236.

Amiti, M. and Konings, J. (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *American Economic Review*, 97(5):1611–1638.

Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American economic review*, 93(1):170–192.

Antón Pérez, J. I., Klenert, D., Fernández-Macías, E., Brancati, M. C. U., and Alaveras, G. (2020). The labour market impact of robotisation in europe. Technical report, JRC Working Papers Series on Labour, Education and Technology.

Antras, P. (2015). *Global production: Firms, contracts, and trade structure*. Princeton University Press.

Arrow, K. J. (1972). *Economic welfare and the allocation of resources for invention*. Springer.

Artuc, E., Christiaensen, L., and Winkler, H. (2019). Does automation in rich countries hurt developing ones?: Evidence from the us and mexico. *Evidence from the US And Mexico (February 14, 2019). World Bank Policy Research Working Paper*, (8741).

Asker, J., Collard-Wexler, A., and De Loecker, J. (2014). Dynamic inputs and resource (mis) allocation. *Journal of Political Economy*, 122(5):1013–1063.

Atkinson, R. D. (2019). Robotics and the future of production and work. Technical report, Information Technology and Innovation Foundation.

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of economic perspectives*, 29(3):3–30.

Bai, C.-E., Hsieh, C.-T., and Song, Z. (2020a). Special deals with chinese characteristics. *NBER macroeconomics annual*, 34(1):341–379.

Bai, C.-E., Hsieh, C.-T., Song, Z. M., and Wang, X. (2020b). The rise of state-connected private owners in china. Technical report, National Bureau of Economic Research.

Bai, Y., Jin, K., and Lu, D. (2018). Misallocation under trade liberalization.

Bai, Y., Jin, K., and Lu, D. (2019). Misallocation under trade liberalization. Technical report, National Bureau of Economic Research.

Bartelsman, E., Haltiwanger, J., and Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American economic review*, 103(1):305–334.

Belton, K. B., Graham, J., and Xia, S. (2020). 'made in china 2025'and the limitations of us trade policy. *Available at SSRN 3664347*.

Beŋkovskis, K. (2015). Misallocation of resources in latvia: Did anything change during the crisis? Technical report, Latvijas Banka Working Paper 5, Riga.

Berezina, K., Ciftci, O., and Cobanoglu, C. (2019). Robots, artificial intelligence, and service automation in restaurants. In *Robots, artificial intelligence, and service automation in travel, tourism and hospitality*, pages 185–219. Emerald Publishing Limited.

Berke, B. (2021). A literature survey on extensive and intensive margins in international trade. *Impact of Global Issues on International Trade*, pages 124–136.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2010). Multiple-product firms and product switching. *American economic review*, 100(1):70–97.

Berrell, M. M. and Wrathall, J. (2003). Changing attitudes to intellectual property rights in china: The nexus between chinese culture and the rule of law. In *Proceedings of the 15th Annual Conference of the Association for Chinese Economic Studies Australia (ACESA)(Melbourne, VIC)*.

Berthou, A., Chung, J. J., Manova, K., and Bragard, C. S. D. (2018). Productivity,(mis) allocation and trade. Technical report, Mimeo.

Bérubé, C. and Mohnen, P. (2009). Are firms that receive r&d subsidies more innovative? *Canadian Journal of Economics/Revue canadienne d'économique*, 42(1):206–225.

Blaum, J., Lelarge, C., and Peters, M. (2017). Firm size and the intensive margin of import demand.

Blöcher, K. and Alt, R. (2021). Ai and robotics in the european restaurant sector: Assessing potentials for process innovation in a high-contact service industry. *Electronic Markets*, 31:529–551.

Bloom, N., Van Reenen, J., and Williams, H. (2019). A toolkit of policies to promote innovation. *Journal of economic perspectives*, 33(3):163–184.

Bonfiglioli, A., Crinò, R., Fadinger, H., and Gancia, G. (2020). Robot imports and firm-level outcomes.

Borjas, G. J. and Freeman, R. B. (2019). From immigrants to robots: The changing locus of substitutes for workers. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 5(5):22–42.

Bosworth, D. and Yang, D. (2000). Intellectual property law, technology flow and licensing opportunities in the people's republic of china. *International Business Review*, 9(4):453–477.

Brandt, L., Tombe, T., and Zhu, X. (2013). Factor market distortions across time, space and sectors in china. *Review of Economic Dynamics*, 16(1):39–58.

Brandt, L., Van Biesebroeck, J., Wang, L., and Zhang, Y. (2017). Wto accession and performance of chinese manufacturing firms. *American Economic Review*, 107(9):2784–2820.

Brandt, L., Van Biesebroeck, J., and Zhang, Y. (2012). Creative accounting or creative destruction? firm-level productivity growth in chinese manufacturing. *Journal of development economics*, 97(2):339–351.

Branstetter, L. G., Fisman, R., and Foley, C. F. (2006). Do stronger intellectual property rights increase international technology transfer? empirical evidence from us firm-level panel data. *The Quarterly Journal of Economics*, 121(1):321–349.

Bratti, M. and Conti, C. (2018). The effect of immigration on innovation in italy. *Regional Studies*, 52(7):934–947.

Bronzini, R. and Piselli, P. (2016). The impact of r&d subsidies on firm innovation. *Research Policy*, 45(2):442–457.

Brooks, W. and Wang, J. (2016). The aggregate effects of firm-level trade distortions. *Manuscript, University of Notre Dame*.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and development: A tale of two sectors. *American economic review*, 101(5):1964–2002.

Bughin, J., Seong, J., Manyika, J., Chui, M., and Joshi, R. (2018). Notes from the ai frontier: Modeling the impact of ai on the world economy. *McKinsey Global Institute*, 4.

Cai, H. and Liu, Q. (2009). Competition and corporate tax avoidance: Evidence from chinese industrial firms. *The Economic Journal*, 119(537):764–795.

Candelin-Palmqvist, H., Sandberg, B., and Mylly, U.-M. (2012). Intellectual property rights in innovation management research: A review. *Technovation*, 32(9-10):502–512.

Chen, C., Tian, W., and Yu, M. (2019). Outward fdi and domestic input distortions: Evidence from chinese firms. *The Economic Journal*, 129(624):3025–3057.

Chen, K. and Irarrazabal, A. (2015). The role of allocative efficiency in a decade of recovery. *Review of Economic Dynamics*, 18(3):523–550.

Chen, Y. and Puttitanun, T. (2005). Intellectual property rights and innovation in developing countries. *Journal of development economics*, 78(2):474–493.

Chen, Z. and Zhang, J. (2019). Types of patents and driving forces behind the patent growth in china. *Economic Modelling*, 80:294–302.

Chen, Z., Zhang, J., and Zheng, W. (2017). Import and innovation: Evidence from chinese firms. *European Economic Review*, 94:205–220.

Cheng, H., Jia, R., Li, D., and Li, H. (2019). The rise of robots in china. *Journal of Economic Perspectives*, 33(2):71–88.

Chiacchio, F., Petropoulos, G., and Pichler, D. (2018). The impact of industrial robots on eu employment and wages: A local labour market approach. Technical report, Bruegel working paper.

Chung, J. H. (2018). Firm heterogeneity, misallocation, and trade.

Cockburn, I. M., Henderson, R., and Stern, S. (2019). 4. the impact of artificial intelligence on innovation: An exploratory analysis. In *The economics of artificial intelligence*, pages 115–148. University of Chicago Press.

Costa-Scottini, L. (2018). Firm-level distortions, trade, and international productivity differences. Technical report, Working paper, Brown University.

Dai, M. and Yu, M. (2013). Firm r&d, absorptive capacity and learning by exporting: Firm-level evidence from china. *The World Economy*, 36(9):1131–1145.

De Loecker, J. and Syverson, C. (2021). An industrial organization perspective on productivity. In *Handbook of industrial organization*, volume 4, pages 141–223. Elsevier.

Defever, F. and Riaño, A. (2017). Subsidies with export share requirements in china. *Journal of Development Economics*, 126:33–51.

Deng, P., Lu, H., Hong, J., Chen, Q., and Yang, Y. (2019). Government r&d subsidies, intellectual property rights protection and innovation. *Chinese Management Studies*, 13(2):363–378.

DeStefano, T. and Timmis, J. (2021). Robots and export quality.

Di Giovanni, J., Levchenko, A. A., and Ranciere, R. (2011). Power laws in firm size and openness to trade: Measurement and implications. *Journal of International Economics*, 85(1):42–52.

Ding, S., Jiang, W., and Sun, P. (2016). Import competition, dynamic resource allocation and productivity dispersion: micro-level evidence from china. *Oxford Economic Papers*, 68(4):994–1015.

Dixon, J., Hong, B., and Wu, L. (2020). *The employment consequences of robots: Firm-level evidence*. Statistics Canada Ontario.

Du, Y. and Wei, X. (2022). Technological change and unemployment: evidence from china. *Applied Economics Letters*, 29(9):851–854.

Eberhardt, M., Helmers, C., and Yu, Z. (2011). Is the dragon learning to fly? an analysis of the chinese patent explosion. *An Analysis of the Chinese Patent Explosion (November 29, 2011). The University of Nottingham Research Paper*, (2011/16).

Eberhardt, M., Helmers, C., and Yu, Z. (2016). What can explain the chinese patent explosion? *Oxford Economic Papers*, 69(1):239–262.

Evangelista, R. and Savona, M. (2003). Innovation, employment and skills in services. firm and sectoral evidence. *Structural Change and Economic Dynamics*, 14(4):449–474.

Faber, M. (2020). Robots and reshoring: Evidence from mexican labor markets. *Journal of International Economics*, 127:103384.

Faia, E., Laffitte, S., Mayer, M., and Ottaviano, G. (2021). On the employment consequences of automation and offshoring: A labor market sorting view. In *Robots and AI*, pages 82–122. Routledge.

Fan, H., Hu, Y., and Tang, L. (2021). Labor costs and the adoption of robots in china. *Journal of Economic Behavior & Organization*, 186:608–631.

Fan, H., Lai, E. L.-C., and Qi, H. S. (2019). Trade liberalization and firms' export performance in china: Theory and evidence. *Journal of Comparative Economics*, 47(3):640–668.

Fang, L., Lerner, J., Wu, C., and Zhang, Q. (2018). Corruption, government subsidies, and innovation: Evidence from china. Technical report, National Bureau of Economic Research.

Fang, L. H., Lerner, J., and Wu, C. (2017). Intellectual property rights protection, ownership, and innovation: Evidence from china. *The Review of Financial Studies*, 30(7):2446–2477.

Fassio, C., Montobbio, F., and Venturini, A. (2019). Skilled migration and innovation in european industries. *Research Policy*, 48(3):706–718.

Feenstra, R. and Ma, H. (2007). Optimal choice of product scope for multiproduct firms under monopolistic competition. Technical report, National Bureau of Economic Research.

Fernandes, A. M., Klenow, P. J., Meleshchuk, S., Pierola, D., and Rodriguez-Clare, A. (2018). The intensive margin in trade. Technical report, National Bureau of Economic Research.

Frietsch, R. and Wang, J. (2007). Intellectual property rights and innovation activities in china: evidence from patents and publications. Technical report, Fraunhofer ISI Discussion Papers-Innovation Systems and Policy Analysis.

Fu, X. (2008). Foreign direct investment, absorptive capacity and regional

innovation capabilities: evidence from china. *Oxford development studies*, 36(1):89–110.

Gan, J., Liu, L., Qiao, G., and Zhang, Q. (2023). The role of robot adoption in green innovation: Evidence from china. *Economic Modelling*, 119:106128.

Gao, Y., Whalley, J., and Ren, Y. (2014). Decomposing china's export growth into extensive margin, export quality and quantity effects. *China economic review*, 29:19–26.

García-Santana, M., Moral-Benito, E., Pijoan-Mas, J., and Ramos, R. (2016). Growing like spain: 1995-2007.

Garcia-Vega, M., Kneller, R., and Stiebale, J. (2021). Labor market reform and innovation: Evidence from spain. *Research Policy*, 50(5):104213.

Girma, S., Greenaway, D., and Kneller, R. (2002). *Does Exporting Lead to Better Performance?: A Microeconometric Analysis of Matched Firms*. Leverhulme Centre for research on globalisation and economic policy.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly journal of economics*, 125(4):1727–1767.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., and Villegas-Sanchez, C. (2017). Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, 132(4):1915–1967.

Gopinath, G. and Neiman, B. (2014). Trade adjustment and productivity in large crises. *American Economic Review*, 104(3):793–831.

Gorodnichenko, Y., Svejnar, J., and Terrell, K. (2010). Globalization and innovation in emerging markets. *American Economic Journal: Macroeconomics*, 2(2):194–226.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Grossman, G. M. and Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European economic review*, 35(2-3):517–526.

Hall, B. H. (2007). Patents and patent policy. *Oxford Review of Economic Policy*, 23(4):568–587.

Hall, B. H. and Rosenberg, N. (2010). *Handbook of the Economics of Innovation*. Elsevier.

Halpern, L., Koren, M., and Szeidl, A. (2015). Imported inputs and productivity. *American Economic Review*, 105(12):3660–3703.

Haltiwanger, J., Kulick, R., and Syverson, C. (2018). Misallocation measures: The distortion that ate the residual. Technical report, National Bureau of Economic Research.

He, A. (2021). What do china's high patent numbers really mean? *Center for International Governance Innovation*.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, 64(4):605–654.

Helpman, E. and Krugman, P. (1987). *Market structure and foreign trade: Increasing returns, imperfect competition, and the international economy*. MIT press.

Ho, G. T. (2010). Trade liberalization with idiosyncratic distortions: Theory and evidence from india. Technical report.

Hopenhayn, H. and Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy*, 101(5):915–938.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448.

Hsieh, C.-T. and Song, Z. M. (2015). Grasp the large, let go of the small: The transformation of the state sector in china. Technical report, National Bureau of Economic Research.

Hu, A. G. and Jefferson, G. H. (2009). A great wall of patents: What is behind china's recent patent explosion? *Journal of Development Economics*, 90(1):57–68.

Hu, A. G., Zhang, P., and Zhao, L. (2017). China as number one? evidence from china's most recent patenting surge. *Journal of Development Economics*, 124:107–119.

Huang, G., He, L.-Y., and Lin, X. (2022). Robot adoption and energy performance: Evidence from chinese industrial firms. *Energy Economics*, 107:105837.

Ivanov, S. H. and Webster, C. (2017). Adoption of robots, artificial intelligence and service automation by travel, tourism and hospitality companies–a cost-benefit analysis. *Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies–A Cost-Benefit Analysis*.

Jaffe, A. B. and Le, T. (2015). The impact of r&d subsidy on innovation: a study of new zealand firms. Technical report, National Bureau of Economic Research.

Jones, C. I. (2011). Intermediate goods and weak links in the theory of economic development. *American Economic Journal: Macroeconomics*, 3(2):1–28.

Khandelwal, A. K., Schott, P. K., and Wei, S.-J. (2013). Trade liberalization and embedded institutional reform: evidence from chinese exporters. *American Economic Review*, 103(6):2169–95.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638):2553–2584.

Kong, D., Tao, Y., and Wang, Y. (2020). China's anti-corruption campaign and firm productivity: Evidence from a quasi-natural experiment. *China Economic Review*, 63:101535.

Krugman, P. R. (1979). Increasing returns, monopolistic competition, and international trade. *Journal of international Economics*, 9(4):469–479.

Krugman, P. R. (1987). Is free trade passé? *Journal of economic Perspectives*, 1(2):131–144.

Kugler, A. D., Kugler, M., Ripani, L., and Rodrigo, R. (2020). Us robots and their impacts in the tropics: Evidence from colombian labor markets. Technical report, National Bureau of Economic Research.

Kunz, W. H., Heinonen, K., and Lemmink, J. G. (2019). Future service technologies: is service research on track with business reality? *Journal of Services Marketing*, 33(4):479–487.

Li, H., Li, L., Wu, B., and Xiong, Y. (2012). The end of cheap chinese labor. *Journal of Economic Perspectives*, 26(4):57–74.

Li, X. (2012). Behind the recent surge of chinese patenting: An institutional view. *Research policy*, 41(1):236–249.

Lin, C., Xiao, S., and Yin, Z. (2022). How do industrial robots applications affect the quality upgrade of chinese export trade? *Telecommunications Policy*, 46(10):102425.

Lin, J., Wu, H.-M., and Wu, H. (2021). Could government lead the way? evaluation of china's patent subsidy policy on patent quality. *China Economic Review*, 69:101663.

Liu, Q., Lu, R., Lu, Y., and Luong, T. A. (2021). Import competition and firm innovation: Evidence from china. *Journal of Development Economics*, 151:102650.

Liu, Q. and Qiu, L. D. (2016). Intermediate input imports and innovations: Evidence from chinese firms' patent filings. *Journal of International Economics*, 103:166–183.

Long, C. X. and Wang, J. (2019). China's patent promotion policies and its quality implications. *Science and Public Policy*, 46(1):91–104.

López, R. A. and Yadav, N. (2010). Imports of intermediate inputs and spillover effects: Evidence from chilean plants. *The Journal of Development Studies*, 46(8):1385–1403.

Lu, Y. and Ng, T. (2012). Do imports spur incremental innovation in the south? *China Economic Review*, 23(4):819–832.

Manova, K. (2012). Credit constraints, heterogeneous firms, and international trade. *Review of Economic Studies*, 80(2):711–744.

Manova, K. and Yu, Z. (2016). How firms export: Processing vs. ordinary trade with financial frictions. *Journal of International Economics*, 100:120–137.

Markusen, J. R. (1989). Trade in producer services and in other specialized intermediate inputs. *The American Economic Review*, pages 85–95.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725.

Melitz, M. J. and Polanec, S. (2015). Dynamic olley-pakes productivity decomposition with entry and exit. *The Rand journal of economics*, 46(2):362–375.

Melitz, M. J. and Trefler, D. (2012). Gains from trade when firms matter. *Journal of Economic Perspectives*, 26(2):91–118.

Midrigan, V. and Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American economic review*, 104(2):422–458.

Muehlfeld, K. and Wang, M. (2022). Intellectual property rights in china—a literature review on the public's perspective. *Frontiers in Sociology*, 7:793165.

Naghavi, A. and Strozzi, C. (2015). Intellectual property rights, diasporas, and domestic innovation. *Journal of International Economics*, 96(1):150–161.

Papageorgiadis, N. and Sharma, A. (2016). Intellectual property rights and innovation: A panel analysis. *Economics Letters*, 141:70–72.

Prud'homme, D. and Zhang, T. (2019). Chinese patenting trends and the role of the state. In *China's Intellectual Property Regime for Innovation*, pages 43–71. Springer.

Ramanarayanan, A. (2020). Imported inputs and the gains from trade. *Journal of International Economics*, 122:103260.

Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics*, 11(4):707–720.

Restuccia, D. and Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3):151–74.

Robinson, J. A. and Acemoglu, D. (2012). *Why nations fail: The origins of power, prosperity and poverty*. Profile London.

Rodrik, D. (2018). New technologies, global value chains, and developing economies. Technical report, National Bureau of Economic Research.

Sandoz, C. (2017). Input prices, allocation of resources and tfp growth: Evidence from chinese imports in france.

Sharif, N. and Huang, Y. (2019). Industrial automation in china's "workshop of the world". *The China Journal*, 81(1):1–22.

Song, Z., Storesletten, K., and Zilibotti, F. (2011). Growing like china. *American economic review*, 101(1):196–233.

Song, Z. and Wu, G. L. (2015). Identifying capital misallocation. *Work. Pap., Univ. Chicago, Chicago*.

Spence, M. (1986). Cost reduction, competition and industry performance. In *New developments in the analysis of market structure: Proceedings of a conference held by the international economic association in Ottawa, Canada*, pages 475–518. Springer.

Stapleton, K. (2020). *Essays on technology, trade and labour markets*. PhD thesis, University of Oxford.

Stapleton, K. and Webb, M. (2020). Automation, trade and multinational activity: Micro evidence from spain. *Available at SSRN 3681143*.

Storesletten, K. and Zilibotti, F. (2014). China's great convergence and beyond. *Annu. Rev. Econ.*, 6(1):333–362.

Sweet, C. M. and Maggio, D. S. E. (2015). Do stronger intellectual property rights increase innovation? *World Development*, 66:665–677.

Syverson, C. (2011). What determines productivity? *Journal of Economic literature*, 49(2):326–365.

Tombe, T. and Zhu, X. (2019). Trade, migration, and productivity: A quantitative analysis of china. *American Economic Review*, 109(5):1843–72.

Toner, P. (2011). Workforce skills and innovation: An overview of major themes in the literature.

Topalova, P. and Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of india. *Review of economics and statistics*, 93(3):995–1009.

Trantopoulos, K., von Krogh, G., Wallin, M. W., and Woerter, M. (2017). External knowledge and information technology. *MIS quarterly*, 41(1):287–300.

Vandenbussche, H. and Viegelahn, C. (2016). Input reallocation within firms.

vom Brocke, J., Zelt, S., and Schmiedel, T. (2016). On the role of context in business process management. *International Journal of Information Management*, 36(3):486–495.

Wang, J. (2021). Robots, trade, and offshoring: A perspective from us firms. *Unpublished Manuscript, Harvard University*.

Wang, L., Wang, Y., and Zhou, J. (2022). Political connection, government r&d subsidies and innovation efficiency: Evidence from china. *Finance Research Letters*, 48:102953.

Wang, W. (2017). Intermediate goods and misallocation in china's manufacturing sector. Technical report, Working Paper.

Wechsler, A. (2011). Intellectual property law in the people's republic of china: a powerful economic tool for innovation and development. *China-EU Law Journal*, 1:3–54.

Wu, G. L. (2018). Capital misallocation in china: Financial frictions or policy distortions? *Journal of Development Economics*, 130:203–223.

Wu, R., Liu, Z., Ma, C., and Chen, X. (2020). Effect of government r&d subsidies on firms' innovation in china. *Asian Journal of Technology Innovation*, 28(1):42–59.

Xu, C. (2011). The fundamental institutions of china's reforms and development. *Journal of economic literature*, 49(4):1076–1151.

Yang, Z. (2017). Who will satisfy china's thirst for industrial robots? *The Diplomat*.

Yu, H. (2018). Robot threat or robot dividend?: A struggle between two lines. *Made in China Journal*, 3(2):50–55.

Yu, M. (2015). Processing trade, tariff reductions and firm productivity: Evidence from chinese firms. *The Economic Journal*, 125(585):943–988.

Zhang, L., Gan, T., and Fan, J. (2023). Do industrial robots affect the labour market? evidence from china. *Economics of Transition and Institutional Change*, 31(3):787–817.

Zhao, Y., Said, R., Ismail, N. W., and Hamzah, H. Z. (2022). Effect of industrial robots on employment in china: an industry level analysis. *Computational Intelligence and Neuroscience*, 2022.

Żukrowska, K. (2021). Artificial intelligence (ai) and international trade. *Artificial Intelligence and Its Contexts: Security, Business and Governance*, pages 225–240.

Appendices

Appendix A

Theoretical framework

Consumer preference: the model economy consists of two countries, Home(H) and Foreign(F), and each country $i, j \in H, F$ is inhabited by L_i identical consumers who supply one unit of labor inelasticity and X_i quantity of intermediate inputs. A representative consumer in each country has Dixit-stiglit preferences with constant elasticity of substitution $\sigma > 1$. For all variables, the first subscript denotes where the goods are produced and the second subscript denotes where the goods are consumed.

A.1 Closed economy heterogeneous firm model

Utility in Home country using a CES form is given by:

$$U = \left[\int_{\omega \in \Omega} q^{\frac{\sigma-1}{\sigma}}(\omega) d\omega \right]^{\frac{\sigma}{\sigma-1}} \tag{A.1}$$

where Ω is the endogenous set of goods produced in Home. The corresponding demand function is thus:

$$q(\omega) = P^{\sigma-1}Ep^{-\sigma}(\omega) \tag{A.2}$$

where P is the final goods price index, E is the total expenditure of the consumers, and $p(\omega)$ is price of good ω in the market. P an be expressed as:

$$P_i = \left[\int_{\omega\in\Omega} p_{ji}^{1-\sigma}(\omega)\right]^{\frac{1}{\sigma-1}} \tag{A.3}$$

Production: There are potential entrants in the home country that can enter the market by paying a sunk entry cost of f_e units of labour. Then these potential entrants are heterogeneous in terms of their productivity φ, which is drawn from a cumulative distribution $F(\varphi)$. They also learn their idiosyncratic intermediate input wedges τ_x on domestic intermediate inputs and output wedge τ_y, which can be treated as a tax (> 1) or subsidy (< 1). We assume that the output and domestic input wedges are drawn from the cumulative distribution, F_τ, with support $(0, \infty)$. Productivity is assumed to be independent of wedges. let $\omega(\varphi, \tau_y, \tau_x)$ denotes a firm's state vector, and the corresponding cumulative density function for ω is given by $\Gamma(\omega) = F_\varphi \bigotimes F_y \bigotimes F_x$, $\bigotimes$ means the tensor product. After knowing their ω, firms decide whether to stay in or exit the market, then if a firm chooses to stay and operate, it faces strictly positive fixed costs wf.

Firms face monopolistic competition. The firm's production function is expressed as:

$$y(\omega) = \varphi(\omega)x^{\alpha}(\omega)l^{1-\alpha}(\omega) \tag{A.4}$$

A firm thus solves the following problem

$$\max_{p,q} = \frac{pq}{\tau_y} - wl - \tau_x p_x - wf \tag{A.5}$$

subject to the demand function

$$q = EP^{\sigma-1}p^{-\sigma}(\omega) \tag{A.6}$$

henceforward suppressing ω for convenience. Firms are infinitesimally small, and thus take the aggregate price index as given. The equilibrium prices are a constant mark-up over marginal costs:

$$p = \frac{\sigma}{\sigma-1}\tau_y \frac{1}{\varphi}\left(\frac{\tau_x p_x}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha} \tag{A.7}$$

where w and p_x are wage and price if domestic input respectively. Thus the ex-post tax revenue is

$$r = \frac{pq}{\tau_y} \tag{A.8}$$

Optimal profits are then

$$\pi = r - qMC - wf = \left(\frac{p}{\tau_y} - MC\right)q - wf = \left(\frac{p}{\tau_y} - \frac{\sigma-1}{\sigma}\frac{1}{\tau_y}p\right)q - wf = \frac{pq}{\tau_y}\frac{1}{\sigma} - wf = \frac{r}{\sigma} - wf \tag{A.9}$$

The fixed production cost implies a cutoff productivity below which firms exit the market. This cutoff productivity satisfies that

$$\frac{r(\varphi^*(\tau_y,\tau_x))}{\sigma} = \sigma wf \Rightarrow \varphi^*(\tau_{y,x}) = \left(\frac{\sigma wf}{EP^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\left(\frac{\tau_x p_x}{\alpha}\right)^{\alpha}\tau_y^{\frac{\sigma}{\sigma-1}} \tag{A.10}$$

We find that the firms with a higher tax (τ_y and τ_x) will have a higher cutoff productivity to operate. That is to say, low-productive firms may enter the market because of getting sufficient subsidies, at the cost of high-

productive firms with high taxes.

In the situation of the steady-state closed economy equilibrium, the mass of firms entering the market and operating is constant. we assume a constant independent probability of firms' death δ in each period and constant productivity once enters the market. We can get the stationary ex-post distribution for productivity, output distortion, and input distortion $\mu(\varphi, \tau_y, \tau_x)$, which is the truncation of the ex-ante productivity-distortions distribution $\Gamma(\varphi, \tau_y, \tau_x)$ at the operating cutoff productivity expressed by:

$$\mu(\varphi, \tau_y, \tau_x) = \frac{\Gamma(\varphi, \tau_y, \tau_x)}{\int_0^\infty \int_0^\infty \int_{\varphi^*(\tau_y,\tau_x)}^\infty \Gamma(\varphi, \tau_y, \tau_x) d\varphi d\tau_y d\tau_x} \tag{A.11}$$

The denominator is the probability of successful entry G_e.

In the static equilibrium, the free entry condition meets when the expected value of entry with sunk cost in terms of labour, so that

$$G_e \sum_{s=0}^{\infty} (1-\delta)^s E(\pi(\varphi, \tau_y, \tau_x)) = G_e \frac{E(\pi(\varphi, \tau_y, \tau_x))}{\delta} = w f_e \tag{A.12}$$

and the expected value of successful entry $E(\pi(\varphi, \tau_y, \tau_x))$ denoted as:

$$E(\pi(\varphi, \tau_y, \tau_x)) = \int_0^\infty \int_0^\infty \int_{\varphi^*(\tau_y,\tau_x)}^\infty \left(\frac{r}{\sigma} - wf\right) \frac{\Gamma(\varphi, \tau_y, \tau_x)}{G_e} d\varphi d\tau_y d\tau_x \tag{A.13}$$

more specifically, the Free Entry Condition denotes as

$$\begin{aligned} \frac{EP^{\sigma-1}}{\sigma} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \left(\frac{w}{1-\alpha}\right)^{(1-\alpha)(1-\sigma)} \left(\frac{p_x}{\alpha}\right)^{\alpha(1-\sigma)} \iiint_{\varphi^*(\tau_t,\tau_x)} \varphi^{\sigma-1} \tau_y^{-\sigma} \tau_x^{\alpha(1-\sigma)} \Gamma(\varphi, \tau_y, \tau_x) d \\ - wf \iiint_{\varphi^*(\tau_t,\tau_x)} \Gamma(\varphi, \tau_y, \tau_x) d\varphi d\tau_y d\tau_x = \sigma w f_e \end{aligned} \tag{A.14}$$

Let M_e denote the mass of entrants and M the mass of operating firms. A stationary equilibrium with a constant mass of firms in operating implies

that the measure of successful entrants equals the mass of firms that exit. Thus:

$$G_e M_e = \delta M$$

Labour market clearing. Labour used to enter for the mass of entrants:

$$L_e = M_e f_e$$

Labour used for the production of the individual firm:

$$l_p = \frac{1-\alpha}{w\tau_y}\frac{\sigma-1}{\sigma}pq = \frac{1-\alpha}{w\tau_y}\frac{\sigma-1}{\sigma}EP^{\sigma-1}\left(\frac{\sigma}{\sigma-1}\frac{\tau_y}{\varphi}\left(\frac{\tau_x p_x}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}\right)^{1-\sigma}$$
$$= \frac{1-\alpha}{w}EP^{\sigma-1}\left(\frac{\sigma-1}{\sigma}\right)^{-\sigma}\left(\frac{p_x}{\alpha}\right)^{\alpha(1-\sigma)}\left(\frac{w}{1-\alpha}\right)^{(1-\alpha)(1-\sigma)}\varphi^{\sigma-1}\tau_y^{-\sigma}\tau_x^{\alpha(1-\sigma)}$$

The total labour used in production can be expressed by:

$$L_p = M\iiint_{\varphi^*(\tau_y,\tau_x)}^{\infty} l_p\frac{\Gamma(\varphi,\tau_y,\tau_x)}{G_e})d\varphi d\tau_y d\tau_x \tag{A.15}$$

Total labour used in fixed operating cost can be expressed by:

$$L_f = Mf$$

The labour market clearing condition is denoted as:

$$L = L_e + L_p + L_f \tag{A.16}$$

The inputs used in production for an individual firm can be expressed by:

$$x = \frac{\alpha}{\tau_y}\frac{1}{\tau_x p_x}\frac{\sigma-1}{\sigma}pq$$

The input market clearing condition and the total inputs used in production for all operating firms can be expressed by:

$$X = M \iiint_{\varphi^*(\tau_y,\tau_x)}^{\infty} \frac{\alpha}{\tau_y} \frac{1}{\tau_x p_x} \frac{\sigma - 1}{\sigma} pq \frac{\Gamma(\varphi, \tau_y, \tau_x)}{G_e}) d\varphi d\tau_y d\tau_x \tag{A.17}$$

let E denote aggregate expenditure in Home country. The goods market clearing condition:

$$E = wL + p_x X + T \tag{A.18}$$

where T is the total subsidy and tax and can be expressed by:

$$T = M \iiint_{\varphi^*(\tau_y,\tau_x)}^{\infty} \left[\left(1 - \frac{1}{\tau_y} \right) pq + (\tau_x - 1) p_x x \right] \frac{\Gamma(\varphi, \tau_y, \tau_x)}{G_e}) d\varphi d\tau_y d\tau_x$$

A.2 Two-country open economy model

Utility in country i is given by:

$$U_i = \left[\int_{\omega \in \Omega_{ji}} q_{ji}^{\frac{\sigma-1}{\sigma}}(\omega) d\omega \right]^{\frac{\sigma}{\sigma-1}} \quad i, j \in \{H, F\} \tag{A.19}$$

The budget constraint for the representative consumer:

$$st : \int_{\omega \in \Omega_{ji}} p_{ji}(\omega) q_{ji}(\omega) \leq E_i \tag{A.20}$$

where E_i is the total expenditure of consumers in country i. $p_{ji}(\omega)$ is price of variety ω, $q_{ji}(\omega)$ is the level of consumption of variety ω produced in country j and consumed by consumer in country i.

The lagrangian associated the consumer preference is given by:

$$L = \left[\int_{\omega \in \Omega_{ji}} q_{ji}^{\frac{\sigma}{\sigma-1}}(\omega) d\omega \right]^{\frac{\sigma}{\sigma-1}} - \lambda \left(\int_{\omega \in \Omega_{ji}} p_{ji}(\omega) q_{ji}(\omega) d\omega - E_i \right) \tag{A.21}$$

FOC with respct to q_{ji}:

$$\frac{\partial L}{\partial q_{ji}(\omega)} = \frac{\sigma}{\sigma - 1} \left[\int_{\omega \in \omega} q_{ji}^{\frac{\sigma-1}{\sigma}}(\omega) d\omega \right]^{\frac{1}{\sigma-1}} \frac{\sigma - 1}{\sigma} q_{ji}^{\frac{-1}{\sigma}}(\omega) - \lambda p_{ji}(\omega) = 0 \tag{A.22}$$

$$\Rightarrow \left[\int_{\omega \in \omega} q_{ji}^{\frac{\sigma-1}{\sigma}}(\omega) d\omega \right]^{\frac{1}{\sigma-1}} q_{ji}^{\frac{-1}{\sigma}}(\omega) = \lambda p_{ji}(\omega)$$

and

$$\frac{\partial L}{\partial \lambda} = 0$$

From the first FOC, we have for any $\omega, \omega' \in \Omega_{ji}$:

$$\frac{q_{ji}^{\frac{-1}{\sigma}}(\omega)}{q_{ji}^{\frac{1}{\sigma}}(\omega')} = \frac{\lambda p_{ji}(\omega)}{\lambda p_{ji}(\omega')} = \frac{p_{ji}(\omega)}{p_{ji}(\omega')} \tag{A.23}$$

$$\Rightarrow \frac{q_{ji}(\omega')}{q_{ji}(\omega)} = \frac{p_{ji}^{\sigma}(\omega)}{p_{ji}^{\sigma}(\omega')}$$

$$\Rightarrow P_{ji}^{\sigma}(\omega')q_{ji}(\omega') = p_{ji}^{\sigma}(\omega)q_{ji}(\omega)$$

$$\Rightarrow P_{ji}(\omega')q_{ji}(\omega') = p_{ji}^{1-\sigma}(\omega')p_{ji}^{\sigma}(\omega)q_{ji}(\omega) = p_{ji}^{\sigma}(\omega)q_{ji}(\omega)z_{ji}(\omega')p_{ji}^{1-\sigma}(\omega')$$

$$\underbrace{\int_{\omega'\in\Omega_{ji}} p_{ji}(\omega)q_{ji}(\omega)d\omega'}_{E_i} = p_{ji}^{\sigma}(\omega)q_{ji}(\omega)\int_{\omega'\in\Omega_{ji}} p_{ji}^{1-\sigma}(\omega')d\omega' \tag{A.24}$$

then we can get:

$$E_i = p_{ji}^{\sigma}(\omega)q_{ji}(\omega)P_i^{1-\sigma} = P_iU_i \tag{A.25}$$

where P_i is the price index in country i.

$$P_i = \left[\int_{\omega\in\Omega_{ji}} p_{ji}^{1-\sigma}(\omega)\right]^{\frac{1}{\sigma-1}} \tag{A.26}$$

and first-order condition implies the following demand function:

$$q_{ji}(\omega) = P_i^{\sigma-1}E_ip_{ji}^{-\sigma}(\omega) \tag{A.27}$$

Noting that the value of total expenditure of final goods is simple equal to the price times quantity, for individual final variety ω:

$$r_{ji}(\omega) = p_{ji}(\omega)q_{ji}(\omega) = P_i^{\sigma-1}E_ip_{ji}^{1-\sigma}(\omega) \tag{A.28}$$

The ex-post tax revenue for individual variety ω:

$$\frac{r_{ji}(\omega)}{\tau_y} = \frac{p_{ji}(\omega)q_{ji}(\omega)}{\tau_y} = \frac{P_i^{\sigma-1}E_ip_{ji}^{1-\sigma}(\omega)}{\tau_y} \tag{A.29}$$

total expenditure in country i is given by:

$$\int_{\omega\in\Omega_{ji}} r_{ji}(\omega)d\omega = E_i \tag{A.30}$$

Production: with monopolistic competition, a plant producing good ω draws an efficirncy $\varphi(\omega)$, and produces output using labor l and a composite x of intermediate input, according to:

$$y(\omega) = \varphi(\omega)x^{\alpha}(\omega)l^{1-\alpha}(\omega) \tag{A.31}$$

CES form composite inputs:

$$x(\omega) = \left(x_H^{\frac{\theta-1}{\theta}}(\omega) + x_F^{\frac{\theta-1}{\theta}}(\omega)\right)^{\frac{\theta}{\theta-1}} \tag{A.32}$$

where applying x_H and x_F with elasticity of substitution of $\theta > 1$.
We can identify the types of firms in the model according to the markets they sell to and inputs they buy from: in the final goods market, firms could sell domestically by paying fixed cost wf_d and sell to abroad by paying additional wf_f. Firms could use domestic intermediate input x_H with price p_{xH}, and foreign intermediate inputs x_F with price p_{xF} and pay additional foreign intermediate input fixed cost wf_x. Household owns labor and intermediate inputs. Final goods and intermediate goods are tradable. The budget constraint for country i:

$$E_i \leq wL_i + p_{xi}X_i + T_i; i \in \{H, F\} \tag{A.33}$$

In the presence of output and input wedges, I can identify four types of firms in the model according to the market they sell to and whether they use imported intermediate inputs: firms that use only domestic input and sell only domestically (indexed by k_{i1}), firms that source domestically only, and sell final products to both domestic and foreign markets (indexed by k_{i2}), firms that source domestic and foreign, and sell only domestically (indexed by k_{i3}), firms source inputs from both home and foreign, and sell

final products to both domestic and foreign markets (indexed by k_{i4})[1].

The type $k1$ firms' behavior is similar to the firms in the closed economy. Type $k2$ firms sell to both domestic and foreign markets. That is to say, If a domestic firm with only domestic intermediate inputs export to the foreign market, it solves the following problem:

$$\max_{p_{HF}^{k2}, q_{HF}^{k2}} = \frac{p_{HF}^{k2} q_{HF}^{k2}}{\tau_y H} - t_{HF} MC_H^{k2} q_{HF}^{k2} - w_H f_f \tag{A.34}$$

subject to the demand function

$$q_{HF}^{k2} = E_F P_F^{\sigma-1} (p_{HF}^{k2})^{-\sigma} \tag{A.35}$$

where MC_H^{k2} is the marginal cost of type $k2$ firms, P_F and E_F denote the aggregate price index and expenditure in the Foreign country. Equilibrium prices in the export market are a constant multiple of those in the domestic market:

$$p_{HF}^{k2}(\varphi, \tau_{yH}, \tau_{xH}) = \frac{\sigma}{\sigma - 1} \tau_{yH} (\frac{\tau_{xH} p_{xH}}{\alpha})^{\alpha} (\frac{w_H}{1-\alpha})^{1-\alpha}$$

the demand function:

$$q_{HF}^{k2} = E_F P_F^{\sigma-1} (p_{HF}^{k2})^{-\sigma}$$

The optimal profit from serving the foreign market:

$$\begin{aligned}
\pi_{HF}^{k2} &= \frac{r_{HF}^{k2}}{\sigma} - w_H f_f \\
&= \sigma^{-\sigma} (\sigma - 1)^{\sigma-1} E_F P_F^{\sigma-1} \left[\left(\frac{\tau_{xH} p_{xH}}{\alpha} \right)^{\alpha} \left(\frac{w_H}{1-\alpha} \right)^{1-\alpha} \right]^{1-\sigma} t_{HF}^{1-\sigma} \tau_{yH}^{-\sigma} \varphi^{\sigma-1} - w_H f_f
\end{aligned}$$

[1]The extreme cases, i.e., only using foreign intermediate is not included in the model

yields an optimal cutoff for exporting:

$$\varphi^{*,k2}_{HF}(\tau_{yH},\tau_{xH}) = \left(\frac{\sigma w_H f_f}{E_F P_F^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} t_{HF} \left(\frac{w_H}{1-\alpha}\right) \left(\frac{\tau_{xH} p_{xH}}{\alpha}\right)^{\alpha} \tau_{yH}^{\frac{\sigma}{\sigma-1}}$$

Type $k3$ Firms use domestic and foreign intermediate inputs and solve the following problem:

$$\max_{p^{k3}_{HH}, q^{k3}_{HH}} = \frac{p^{k3}_{HH} q^{k3}_{HH}}{\tau_y H} - MC^{k3}_H q^{k3}_{HH} - w_H f_d - w_H f_x \tag{A.36}$$

subject to the demand function

$$q^{k3}_{HH} = E_H P_H^{\sigma-1} (p^{k3}_{HH})^{-\sigma} \tag{A.37}$$

the equilibrium price of selling to the domestic market is given by:

$$p^{k3}_{HH}(\varphi,\tau_{yH},\tau_{xH},\tau_{xF}) = \frac{\sigma}{\sigma-1}\tau_{yH}(\frac{p_{xHF}}{\alpha})^{\alpha}(\frac{w_H}{1-\alpha})^{1-\alpha}$$

the demand function:

$$q^{k3}_{HH} = E_H P_H^{\sigma-1} (p^{k3}_{HH})^{-\sigma}$$

where $p_{xHF} = [(\tau_{xH} p_{xH})^{1-\theta} + (\tau_{xF} t_{HF} p_{xF})^{1-\theta}]^{\frac{1}{1-\theta}}$ The optimal profit from serving the domestic market:

$$\begin{aligned}\pi^{k3}_{HH} &= \frac{r^{k3}_{HH}}{\sigma} - w_H f_d - w_H f_x \\ &= \sigma^{-\sigma}(\sigma-1)^{\sigma-1} E_H P_H^{\sigma-1} \left[\left(\frac{p_{xHF}}{\alpha}\right)^{\alpha} \left(\frac{w_H}{1-\alpha}\right)^{1-\alpha}\right]^{1-\sigma} t_{HF}^{1-\sigma} \tau_{yH}^{-\sigma} \varphi^{\sigma-1} - w_H f_d - w_H f_x\end{aligned}$$

yields an optimal cutoff for exporting:

$$\varphi^{*,k3}_{HH}(\tau_{yH},\tau_{xH},\tau_{xF}) = \left(\frac{\sigma w_H (f_d + f_x)}{E_H P_H^{\sigma-1}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma-1} t_{HF} \left(\frac{w_H}{1-\alpha}\right) \left(\frac{p_{xHF}}{\alpha}\right)^{\alpha} \tau_{yH}^{\frac{\sigma}{\sigma-1}}$$

Type $k4$ Firms with domestic and foreign intermediate inputs, export to the foreign market, and solve the following problem:

$$\max_{p_{HF}^{k4}, q_{HF}^{k4}} = \frac{p_{HF}^{k4} q_{HF}^{k4}}{\tau_y H} - MC_H^{k4} q_{HF}^{k4} - w_H f_f \tag{A.38}$$

subject to the demand function

$$q_{HF}^{k4} = E_F P_F^{\sigma-1} (p_{HF}^{k4})^{-\sigma} \tag{A.39}$$

the equilibrium price of selling to the domestic market is given by:

$$p_{HF}^{k4}(\varphi, \tau_{yH}, \tau_{xH}, \tau_{xF}) = \frac{\sigma}{\sigma - 1} \tau_{yH} (\frac{p_{xHF}}{\alpha})^{\alpha} (\frac{w_H}{1-\alpha})^{1-\alpha} t_{HF}$$

the demand function:

$$q_{HF}^{k4} = E_F P_F^{\sigma-1} (p_{HF}^{k4})^{-\sigma}$$

where p_{xHF} is the price of composite intermediate inputs.
The optimal profit from serving the foreign market:

$$\begin{aligned}
\pi_{HF}^{k4} &= \frac{r_{HF}^{k4}}{\sigma} - w_H f_f \\
&= \sigma^{-\sigma} (\sigma - 1)^{\sigma-1} E_F P_F^{\sigma-1} \left[\left(\frac{p_{xHF}}{\alpha} \right)^{\alpha} \left(\frac{w_H}{1-\alpha} \right)^{1-\alpha} \right]^{1-\sigma} t_{HF}^{1-\sigma} \tau_{yH}^{-\sigma} \varphi^{\sigma-1} - w_H f_f
\end{aligned}$$

yields an optimal cutoff for exporting:

$$\varphi_{HF}^{*,k4}(\tau_{yH}, \tau_{xH}, \tau_{xF}) = \left(\frac{\sigma w_H (f_f)}{E_F P_F^{\sigma-1}} \right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma - 1} t_{HF} \left(\frac{w_H}{1-\alpha} \right) \left(\frac{p_{xHF}}{\alpha} \right)^{\alpha} \tau_{yH}^{\frac{\sigma}{\sigma-1}}$$

The minimum productivity necessary for a firm of all types in the Home country to operate profitably can be expressed as:

$$\varphi_{HH}^{*}(\tau_{yH}, \tau_{xH}, \tau_{xF}) = min\{\varphi_{HH}^{*,k1}, \varphi_{HH}^{*,k2}, \varphi_{HH}^{*,k3}, \varphi_{HH}^{*,k4}\}$$

where $\varphi_{HH}^{*,ki} = \{\varphi : \pi_{HH}^{Ki} = 0\}$

Labour use in production by an individual firm can be expressed as:

$$
\begin{aligned}
l_{pHH}^{k1} &= \frac{1-\alpha}{w_H} E_H p_H^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{\tau_{xH}p_{xH}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} \\
l_{pHH}^{k2} &= l_{pHH}^{k1} \\
l_{pHF}^{k2} &= \frac{1-\alpha}{w_H} E_F p_F^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{\tau_{xH}p_{xH}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} t_{HF}^{1-\sigma} \\
l_{pHH}^{k3} &= \frac{1-\alpha}{w_H} E_H p_H^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{p_{xHF}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} \\
l_{pHH}^{k4} &= l_{pHH}^{k3} \\
l_{pHF}^{k4} &= \frac{1-\alpha}{w_H} E_F p_F^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{p_{xHF}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} t_{HF}^{1-\sigma}
\end{aligned}
$$

The domestic intermediate inputs used by an individual firm in Home country can be expressed as:

$$
\begin{aligned}
x_{HH}^{k1} &= \frac{\alpha}{\tau_{xH}p_{xH}} E_H p_H^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{\tau_{xH}p_{xH}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} \\
x_{HH}^{k2} &= \frac{\alpha}{\tau_{xH}p_{xH}} (E_H p_H^{\sigma-1} + t_{HF}^{1-\sigma} E_F p_F^{\sigma-1}) \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{\tau_{xH}p_{xH}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} \\
x_{HH}^{k3} &= \left(\frac{p_{xHF}}{\tau_{xh}p_{xH}}\right)^{\theta} \frac{\alpha}{p_{xHF}} E_H p_H^{\sigma-1} \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{p_{xHF}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma} \\
x_{HH}^{k4} &= \left(\frac{p_{xHF}}{\tau_{xh}p_{xH}}\right)^{\theta} \frac{\alpha}{p_{xHF}} (E_H p_H^{\sigma-1} + t_{HF}^{1-\sigma} E_F p_F^{\sigma-1}) \left(\frac{\sigma}{\sigma-1}\tau_{yH}\right)^{-\sigma} \left((\frac{p_{xHF}}{\alpha})(\frac{w_H}{1-\alpha})^{1-\alpha}\right)^{1-\sigma}
\end{aligned}
$$