Sheffield University Management School.

China’s Innovation Challenge: Evidence from industry competition, government subsidies and political turnover

Bo Pan

Registration Number: 160243099

Supervised by:

Dr. Junhong Yang

Prof. Shuxing Yin

Dr. Abongeh Tunyi

A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy in Finance

Sheffield University Management School

University of Sheffield

March 2021

Abstract

In this thesis, we investigate the challenge of corporate innovation in China from three aspects: industry competition, government subsidies, and political turnover. Our study enriches the related literature on innovation in the Chinese context by using a large panel of industrial firms.

In chapter 2, we investigate the effect of industry competition on corporate innovation. Using a panel of 555,124 industrial firms over the period from 1998 to 2007, we find that firm-level innovation is negatively associated with industry competition, and the negative relation is stronger in industries that are more dependent on external finance. Further evidence shows that financing constraints tighten the negative effect of competition on innovation. Our study provides clear identification of a causal effect of competition on innovation by using a difference-in-differences (DID) approach that relies on a plausibly exogenous shift in industrial openness to foreign investment and employing instrumental variables (IV) approach that relies on a time-varying instrument for industry competition.

In chapter 3, we explore the impact of government subsidies on corporate innovation. Using a panel of 663,699 industrial firms over the period from 1998 to 2008, we find that government subsidies have a positive direct effect on corporate innovation. I confirm the causal effect of subsidies on innovation by using an IV estimation and a DID specification. The positive direct effect is more pronounced for private firms, financially constrained firms, firms in industries with low external finance dependence (EFD) or high-tech intensiveness, and firms located in cities with low financial development or low foreign direct investment. Furthermore, subsidies have a greater positive indirect effect on innovation activities for firms without subsidies than firms with subsidies. The paper sheds light on the implications of subsidies in innovation.

In chapter 4, we focus on the influence of political turnover on the finance-innovation nexus. Using a panel of 739,672 industrial firms across 305 cities over the period from 2003 to 2014, we find that local political uncertainty arising from local political turnover decreases the positive effect of city-level financial development on corporate innovation while local political turnover alone promotes corporate innovation. The results are robust to the use of various estimation methods. Further evidence shows that the moderating effect played by local political turnover is various across turnover types, political connections and financial constraints. Our findings shed light on how both political and financial systems influence corporate innovation in China with a weak institutional environment.

Declaration

This thesis is the result of my own achievements unless the contents referenced in the text. I am aware of the University's Guidance on the Use of Unfair Means (www.sheffield.ac.uk/ssid/unfair-means). The material contained in the thesis has not been submitted elsewhere for any other degree or qualification in this or any other institution. However, parts of the thesis have been submitted in various workshops and conferences.

Bo Pan
24 March 2021

Statement of Copyright

Acknowledgements

I first would like to thank my supervisor, Dr. Junhong Yang, for his invaluable guidance throughout the entire project and all stages of the thesis. My sincere and deep gratitude goes to him for opening and shaping my academic minds no matter what difficulties I faced in the tough journey. It is a very brilliant experience for me to study with him who strengthens my enthusiasm for finance and its critical thinking. His encouragement and help made me feel more confident to fulfil my PhD research and overcome every obstacle I encountered. Thank you so much for forcing me, sometimes pushing as well as unwavering patience in supervising me over the past four years. This thesis process would also not have been possible without support from you.

I would like to thank my supervisor, Prof. Shuxing Yin, for sharing advice and providing help for my project, which not only benefits my academic research but also my PhD life. She is a very respectable supervisor and kind to offer support to me in the past four years. I also would like to thank my supervisor, Dr. Abongeh Tunyi. Although he joined my supervisory team in the last year of my project, he shows huge enthusiasm in providing help to improve the thesis.

I would like to thank my girlfriend, Caifei Chen, who is currently a PhD student at the Bayes Business School of City, University of London. She loved and supported me during the last year of my PhD. Although we confirmed our relationship in the last year of my PhD, we have known each other more than ten years since we were undergraduates in China. Thank you for your full understanding of the difficulties I faced during my working experience, and being a constant source of motivation and encouragement. Most importantly, she brings happiness to me every day and makes my dull life meaningful. I love you, little dear.

I would like to thank Tianxiang Zhang and Yajie Chen who are my dear colleagues during the hard PhD journey and forever close friends. It is fantastic to work with them. Without their help, I could not persistently carry out the thesis. I extend many thanks to my colleagues in the Management School as their keen academic interest inspires me to keep moving. My PhD time in Sheffield is unforgettable and enriched due to all of you.

I would like to thank Lion and Pancake. They are not only two brother cats but also my buddies to accompany me during the painful and long lockdown period, as I could not go to my office and have to stay at home to work every day. Without them, I could not stick to the thesis.

I would like to give my extremely special thanks to my parents, Shizhong Pan and Suhua Ma, and my sister Yongli Pan for their faith in me. Your love, caring, understanding and continuing support for me to survive all the stress from the crazy PhD journey. My love for you would last forever because we are a family. No words can express how much you all mean to me.

In the end, I would like to thank my other family members and friends who have appeared in my PhD journey. I would like to dedicate all concerned person whom I love.

Bo Pan

24 March 2021

“You can’t solve a problem on the same level that it was created. You have to rise above it to the next level.”

—Albert Einstein

Table of Contents

List of Figures

Chapter Two

Chapter Three

Chapter Four

List of Tables

Chapter Two

Chapter Three

Chapter Four

List of Abbreviations

ADB	Asian Development Bank
AQSIQ	General Administration of Quality Supervision
AR	Anderson-Rubin
CBRC	China Banking Regulatory Commission
CMBC	China Minsheng Bank Corporation
CNRDS	Chinese Research Data Services
CNY	Chinese yuan
CPC	Communist Party of China
CSMAR	China Stock Market & Accounting Research
DID	Difference-in-differences
EFD	External finance dependence
EI	Entropy Index
FD	Financial development
FDI	Foreign direct investment
FI	Natural logarithm of the number of firms
GAAP	Generally Accepted Accounting Principles
GDP	Gross domestic product
GRP	Gross regional product
HHI	Herfindahl-Hirschman Index
HMT	Hong Kong, Macao or Taiwan
IMF	International Monetary Fund
IPC	International patent classification
IPRs	Intellectual property rights
IV	Instrumental variable
LI	Lerner Index

NBS	National Bureau of Statistics
NDRC	National Development and Reform Commission
NPMLT	National Program for Medium- and Long-term Scientific and Technological Development
OECD	Organisation for Economic Co-operation and Development
PCM	Profit-Cost Margin
PCT	Patent Cooperation Treaty
POBC	People’s Bank of China
PPI	Producer price indices
R&D	Research and Development
SIC	State Information Center
SIPO	State Intellectual Property Office
SMEs	Small and medium-sized enterprises
SMTEs	Small and medium technology-based enterprises
SOBs	State-owned banks
SOEs	State-owned enterprises
TRIPS	Agreement on Trade-related Aspects of Intellectual Property Right
WIPO	World Intellectual Property Organization
WTO	World Trade Organization

Chapter 1

Introduction

Chapter 1
Introduction

1.1. Introduction

Innovation is a crucial instrument for business firms to establish competitive advantages and for a country to ensure long-term economic growth (Solow, 1957; Romer, 1990; Porter, 1991; Aghion & Howitt, 1992). However, information problems and high uncertainty risk tend to discourage firms from innovating (Holmstrom, 1989; Aboody & Lev, 2000; Harhoff, 2000).[1] Given these difficulties, scholars tend to explore the ways to promote innovation effectively from various perspectives (Romer, 1990; Aghion & Howitt, 1992; Brown et al., 2009; Acharya & Xu, 2017; Rong et al., 2017). Considering that at this stage China is facing a big assignment to drive its economic development from the type of 'Made in China' to 'Created in China', innovation is becoming an increasingly vital role in the current strategic transition period, the thesis explores some mechanism (industry competition, government subsidies and political turnovers) through which how corporate innovation in China is affected.

Following approximately 40 years of the reform and open-up, especially after the WTO entrance in 2001, the Chinese economy has transformed in almost every aspect. It has gone from being one of the most closed and isolated economies in the world of little relevance to the global economy, and become both highly globalized and the world's second-largest economy. According to the statistics of the International Monetary Fund (IMF), China's nominal Gross

[1] 'Information problems' is an information imbalance in characters of R&D activities between innovators and outside investors (Holmstrom, 1989). Firms with innovation activities own more information than outside investors on the probability of success and the expected return of these projects since firms are reluctant to fully disclose their innovation plans to avoid competitors' imitation and expropriation (Anton & Yao, 2002). Second, Aboody and Lev (2000) suggest that the accounting rules on R&D expenditure also leads to information asymmetry since R&D expenses are charged to expense when incurred, which makes it difficult for external investors to predict the changeable costs and assessment value of innovation activities. The information asymmetry increases the cost of external finance of innovation and then reduces firms' motivation to innovate.

Domestic Product (GDP) was 14.723 trillion US dollars, which has a significant lead over all countries around the world except the US (20..933 trillion US dollars).[2] China's nominal GDP also has maintained a high growth rate of around 10% per annum from 1978 to 2017, higher than that of the major economies around the world.[3] However, the fast growth of China's economy is mainly driven by an extensive economy mode with huge investments, which displays some shortcomings such as low quality, low profits, and high pollution. A large number of firms grow up by making opportunistic strategies and focusing on a short-term horizon. Innovation investments are less attractive to them than pursuing short-term profits such as diversifying in unrelated industries (Rong et al., 2017). Because of rising costs of production factors and serious environmental pollution, China has to explore a new economic growth model. Additionally, there is a concern about China's slowing economic growth. China's GDP growth has slowed below 7% per annum since 2014. To change the old extensive economy and sustain the high growth in the future, in recent years, the importance of innovation has been recognized and innovation-driven (rather than investment-driven) growth type has been emphasized in China. The report of the 18th National Congress of the Communist Party of China (CPC) clearly states that China should implement the strategy of innovation-driven growth type and adhere to the path of independent innovation with Chinese characteristics. The Chinese government has launched many top-down innovation-related policies over the past few decades (Chen & Naughton, 2016). For instance, the State Council of China puts forward the policy of 'National Program for Long- and Medium-Term Scientific and Technological Development' in 2006. To fight against the slowing economic growth rate, the Chinese central

[2] The data is collected from the World Economic Outlook Database, April 2021: https://www.imf.org/en/Publications/WEO/Issues/2021/03/23/world-economic-outlook-april-2021.

[3] According to the *China Statistical Yearbook* 2020 (http://www.stats.gov.cn/tjsj/ndsj/2020/indexch.htm), China's GDP rapidly increases from 0.368 billion Chinese Yuan (CNY) in 1978 to 99.087 trillion CNY in 2019.

government puts forward the strategy of 'Made in China 2025' in 2015 to further promote innovation, especially indigenous innovation.

Because of these incentive policies supported by governments, China's research and development (R&D) has also made tremendous improvement over the past few decades alongside the rapid development of China's economy. For example, according to the report of 'US Science and Engineering Indicators 2020' released by the US National Science Foundation, China is the world's second-largest R&D country after the US.[4] China has ranked second in the world in some key indicators such as R&D investment, output of scientific and technological papers and added value of high-tech manufacturing. Additionally, the report shows the gap between China and the US in R&D spending is closing fast. From 2000 to 2017, R&D spending of the US grew at an average annual rate of 4.3%, while China's R&D spending grew at an average annual rate of more than 17% over the same period. In 2017, China accounted for 23% of the total global R&D spending of $2.2 trillion, which is only behind the US (25%). According to the *China Statistical Yearbook* 2020 issued by the National Bureau of Statistics (NBS) of China, China's R&D spending in 2019 was 2.21 trillion CNY, which accounted for 2.23% of GDP increased by 56.27% from the spending of 1.42 trillion CNY in 2015. The number of invention patents granted in China (452,804) also ranked 1st in the world. These continuous R&D endeavour makes that China's innovation ability is moving from a quantitative accumulation to a qualitative leap. Specifically, in the latest report of 'Global Innovation Index 2020' published by the World Intellectual Property Organization (WIPO), China ranked 14th of the innovation capability index in 2020.[5] A country that ranks among the

[4] The report of 'US Science and Engineering Indicators 2020' could be browsed through the website address: https://ncses.nsf.gov/pubs/nsb20201.

[5] The report of 'Global Innovation Index 2020' could be browsed through the website address: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2020.pdf.

top 15 in the innovation capability index is generally considered to be an innovative country and China is the only middle-income economy in the top 30.

Although China's innovation has made many achievements over the past few decades, it still faces many shortcomings such as a weak input-output efficiency, a lack of basic research and an overwhelming dependence on foreign technology. Specifically, first, the transformation rate of scientific and technological achievements in China is only around 20%, which is far lower than the 40% rate of developed countries.[6] Second, the *China Statistical Yearbook* 2020 shows that in 2019, the R&D spending in basic research is 133.56 billion CNY, which only occupies approximately 6.03% of the total R&D spending (2.21 trillion CNY). However, the US spends about 20% of its total R&D on basic research. As the main body of R&D activities, the innovation ability of enterprises represents national competitiveness. The R&D intensity of 'above-scale' industrial enterprises in China is only 0.76%, which is still far behind developed countries whose level is from 2.5% to 4%. The low R&D intensity of Chinese enterprises reflects their participation in innovation is not high. Third, facing criticism for its lack of initial innovation ability, China is often portrayed as a land of copycats, where the protection of intellectual property rights (IPRs) are poorly enforced (Allen et al., 2005 Ang et al., 2014). For example, until the end of 2020, the US has taken six 'Section 301 investigations' to target China and nearly all of them as well as Trump's China tariffs starting from 2018 involve the field of China's intellectual property protection. The phrase 'Made in China' is often thought of as cheap, low-quality and counterfeit goods. Overall, the necessity of understanding the obstacles behind China's innovation represents a compelling study.

Meanwhile, the 'reform and opening up' of more than 40 years makes that China changed dramatically in the past few decades, no matter in its economic development, financial

[6] The data is collected from the official website of China Intellectual Property: http://www.chinaipmagazine.com/index.asp.

system or political system. Specifically, China has changed to the second-largest economy, constructed its financial system and abolished its 'life tenure for leaders' system. However, as the largest emerging market and the largest communist country, China still owns some disadvantages (or characters) which are significantly different from western countries, such as an imbalance in economic development, a 'lending discrimination' in the financial market, and a unique appointment system for local officials.[7] Considering that innovation is the key driver of long-term economic growth and China' innovation still faces some shortcomings in its unique financial system and political system, we would like to discuss the mechanisms of corporate innovation in China from the three aspects of industry competition, government subsidies and political turnover, which could be beneficial to China's innovation activities in the future.

1.2. The motivation of this thesis

Innovation is a very important factor in economic development. Although China's innovation has made an impressive development with the big surge of China' economy over the past few decades, China's innovation still faces some challenges. First, China is still an underdeveloped market although China has become the second-largest economy and the largest manufacturing entity around the world. China's market still has some limitations, such as the

[7] China's economic development faces a regional imbalance. Compared to the central and western regions, the Eastern (Costal) region plays a key role in China's economy. For example, according to the *China Statistical Yearbook* 2020 (http://www.stats.gov.cn/tjsj/ndsj/2020/indexch.htm), in 2019 the GDP of the coastal region (53.607 trillion CNY) is about 54.230% of the whole national GDP (99.087 trillion CNY). In addition, because the unique financial system in China is controlled by the state capitals, compared to other types of enterprises such as private firms or foreign firms, state-owned enterprises are more likely to obtain funds from the banking system controlled by the state capitals. As China is a nation governed by the communist party, the local leaders in China must be members of the CPC and their appointment must be decided by higher CPC committees, which is distinct from the western democratic election system.

'lending discrimination' in the financial market and unbalanced economic development. At this stage, China's economy is facing big pressure from its gradually slowing GDP growth rate caused by higher costs of production factors, the shock of the COVID-19 pandemic and increasing global trade protectionism. How to stimulate corporate innovation to drive the economy during China's economic transformation period from a type of producing low-value goods to a type of making high-value goods is very important. Second, although China' market has changed dramatically as China has enjoyed 40 years of benefits from the policy of 'reform and open-up', China's financial market and the political system are still distinct from those in western countries but can largely affect firms' decisions into innovation investments. Thus, investigating the effect of some economic factors from China's unique financial system and political system on corporate innovation is crucial. Third, although substantial previous studies have deeply explored the factors related to innovation, the majority of them tend to prefer western economies (Acharya & Subramanian, 2009; Brown et al., 2009; Aghion et al., 2013; Acharya and Xu, 2017; Acemoglu et al., 2018). The studies which focus on emerging markets, especially China, are still not completely consolidated. These motivations enable us to investigate China's innovation.

Specifically, first, during the past 40 years of 'reform and open-up', China maintained a very high growth rate in terms of GDP and attracted more capitals (including domestic and foreign) into China's market. Thus, there has been a tremendous surge of enterprises in China's market to compete for profits and China's market is characterized by fierce competition than ever before. Since Schumpeter (1911) began to explore the impact of competition on innovation, many studies have investigated it (Scherer, 1967; Nickell, 1996; Blundell et al., 1999; Aghion et al., 2005; Hashmi, 2013). Schumpeter (1943) proposes the 'Schumpeterian effect' theory that predicts a typically negative correlation between competition and innovation and several studies also have developed a nonlinear relationship of U-inverted shape between competition and innovation (Levin et al., 1985; Aghion et al., 2005; Tingvall & Poldahl, 2006; Hashmi, 2013). However, the previous papers focus on developed economies and the research focus on China is still sparse, which leads us to explore what is the role of competition on innovation in China under the background of the big change in China's market competition caused by the 'reform and open-up'. It deserves more in-depth studies to test whether the 'Schumpeterian effect' theory or the U-inverted shape applies to China.

Second, although China has claimed that it gradually from the old planned economic system to a new market economic system, governments still play a key role in the financial market and significantly affect firms' behaviours including innovation investments. As one of the four most important financing sources for firms in China (Allen et al.,2005) and one important economic intervention tool implemented by governments, subsidies have a large impact on firms' innovation activities. Thus, it is worth investigating the role of subsidies on the big improvement of China's innovation over recent decades, especially considering that there is a global debate about whether subsidies allocated by governments could give an unfair advantage to Chinese firms to compete with their foreign counterparts (Godement et al., 2011; Hormats, 2011; Fang & Walsh, 2018).

Third, since China is the largest communist country in the world, China's political system is significantly different from that in western countries whose political government leaders usually come from various political parties and are democratically elected by voters (the 'electorate'). The Communist Party of China (CPC) has absolute power at any time to assign its members to local governments as local government leaders for specific targets. Thus, it motivates us to explore what is the effect of local political turnovers on corporate innovation in China's unique political system. Additionally, considering that China's financial market has developed dramatically since the year 1984 and external financing sources such as loans from the banking system are important to firms' innovation funds, it is interesting to explore the effect of local political turnover on the finance-innovation nexus in the Chinese context.

1.3. The purpose of this thesis

Due to China's unique financial system and political system, the thesis explores the effect of industry competition, government subsidies and political turnover on corporate innovation in China based on a large panel of industrial firms over the period from 1998 to 2014. The understanding of the impact of industry competition, government subsidies and political turnover on corporate innovation is an important issue from both management and academic perspectives. Specifically, first, since China is now facing severe competition, understanding the impact of competition on corporate innovation in China not only can provide some policy implications to governments to efficiently regulate the market to boost innovation investments, but also complementary to the literature on competition and innovation. Second, understanding the impact of government subsidies on corporate innovation in China can lead policymakers to reasonably use subsidy tools to encourage firms to innovate, which also can inspire other emerging markets to how to adopt government tools to stimulate corporate innovation. Third, considering that China's economy can change dramatically from a laggard to a leader in a few short decades with a unique political system that is distinct from that in western countries, understanding the impact of political turnover on finance and innovation nexus in China can enrich the literature on political uncertainty and innovation, which also shows China's unique political mechanism through which how corporate innovation is affected.

The main firm-level data I used in the thesis is mainly from the National Bureau of Statistics (NBS) of China which is an official administration department directly controlled by the State Council of China to take charge of national statistics. The dataset is the most comprehensive dataset of Chinese firms. Specifically, The dataset records the information on all ‘above-scale’ enterprises which have annual sales of more than 5 million CNY, including financial data, establishment years, registration type, etc. From 1998 to 2014, the raw dataset records the information on more than 4.5 million observations covering about 1.1 million firms. In the dataset, approximately 95% of firms are unlisted and only 5% are listed. Using the microeconomic-level data provided by the dataset has many advantages. First, aggregation problems in estimation results can be eliminated. Second, since the NBS is the central department to carry out the national statistics, the potential manipulation by local authorities could be avoided. Third, firm heterogeneity can be considered by using a large sample of firms across the whole nation. We also collect the related data used in the thesis from the State Intellectual Property Office (SIPO), the Chinese Research Data Services (CRDS), the China Stock Market & Accounting Research (CSMAR), the China Statistical Yearbook, the China City Statistical Yearbook, etc.

The structure of the thesis is organized as follows. Chapter 2 explores whether firms’ innovation activities is affected by increased industry competition in China. Chapter 3 investigates the role of government subsidies in firms’ innovation activities in China. Chapter 4 tests how local political turnovers affect the finance and innovation nexus in China. Chapter 5 concludes.

Chapter 2

China’s innovation hurdle: competition and finance

Using a panel of 555,124 industrila firms from 1998 to 2007, this study investigates the extent to which industry competition affects firms’ innovation activities in China. We find that firm-level innovation is negatively related to industry competition, and the negative relation is stronger in higher external finance dependence (EFD) industries. Further evidence shows that the enhanced negative effect in higher EFD industries is more pronounced for financially constrained firms compared to financially healthier counterparts. To mitigate endogeneity concerns and identify the causality between innovation and competition, we exploit the exogenous shift on industrial openness for foreign investments in a difference-in-differences (DID) setting due to China’s WTO accession in 2001. Our findings suggest that firms in industries with a reduction in foreign investment restrictions are less likely to innovate. The results are robust to the use of various specifications and estimation methods. Our paper provides new insights into the real effects of competition and finance on innovation.

Chapter 2
China’ innovation hurdle: competition and finance

2.1. Introduction

China’s economic rise in the past thirty years has been mainly driven by investment and a global trade surplus, displaying some shortcomings, such as low quality, low profits, and high pollution. A large number of firms have grown up by following opportunistic strategies and focusing on short-term profits, such as diversifying into unrelated industries, which discourages their innovation investment (Rong et al., 2017). There is now concern about China’s sustainable economic growth. Moving into an innovation-driven growth model has been prioritizing. China has launched many top-down innovation-related policies (Chen & Naughton, 2016).[8] While innovation in China has made tremendous strides,[9] it still faces various challenges to catch up with developed countries in respect of core technologies. For example, statistics show that in 2015 the number of researchers per 1,000 employees in China was only 2.09. This figure is lower than the average value (8.29) of all members of the Organisation for Economic Co-operation and Development (OECD) and that of most developing economies such as Argentina (2.93), Poland (3.61), and Latvia (4.07). Regarding its number of triadic patent families, in 2015 China had 2,889 and was far behind most of the developed economies such as the EU (13,599), the US (14,886), and Japan (17,360).[10] To shed light on the understanding of China’s innovation challenge, in this study, we investigate the

[8] For instance, the State Council of China put forward a ‘National Program for Long- and Medium-Term Scientific and Technological Development’ in 2006. To fight against the slowing economic growth rate, the Chinese government adopted a ‘Made in China 2025’ strategy in 2015 to promote innovation. Innovation is later emphasized as the key engine for China’s sustained economic growth in the 13th Five-Year Plan in March 2016.

[9] According to OECD reports (2018), China’s gross spending on research and development (R&D) increased from 0.725% of GDP (1991) to 1.445% (2008) and even to 2.118% (2016). China’s total gross spending on R&D in 2016 is 411,993 million US dollars, which is higher than that of most of the developed economies, including the EU (350,297 million US dollars) but only lower than that of the US (464,324 million US dollars). In addition, the OECD (2017) shows that China’s business enterprise R&D expenditure dramatically increased from 19,030 million US dollars (2000) to 305,501 million US dollars (2015).

[10] These disadvantages suggest a low return on R&D spending in China and a weak input-output efficiency of China’s innovation activities.

extent to which industry competition affects firms' innovation activities.[11] Furthermore, we explore two important financial channels [industry-level external finance dependence (EFD) and firm-level financing constraints] through which industry competition challenges firms' innovation activities.

Dating back to at least as far as Schumpeter (1943), the literature documents that competition is one of the crucial factors that drive innovation (e.g., Blundell et al., 1999; Hashmi, 2013). However, the relationship between innovation and competition seems to be contradicted by empirical evidence. Aghion et al. (2005) argue that the relationship between innovation and competition depends on the level of competition. Specifically, they show the two effects operating step by step. At the first step, in 'neck-and-neck' sectors when market competition is not severe, the 'escape-competition effect' dominates. Thus, innovation rises with more competition. In the second step, in 'laggard-and-laggard' (or 'less neck-and-neck') sectors when market competition is intense, the 'selection effect' or 'Schumpeterian effect' dominates. Therefore, more competition decreases innovation.

In China, there has been a considerable change in the intensity of industrial competition. Before 1978, Chinese firms faced less market competition due to the domination of the state-owned capital market, the mandatory planning economy, and the seclusion policy. Many central policies had been issued over time, including the policy of 'reform and opening-up' in 1978, and the State Council guidelines in 2005 and 2010, not only greatly spurred China's economic development but also increased competition by promoting different types of ownership structures e.g., the "Hybrid Sector" firms (Allen et al., 2015).[12] Increased competition is also a result of low barriers to entry (Allen et al., 2015). Allen et al. (2005) show

[11] A growing body of literature has explored the factors driving innovation from various perspectives, e.g. the role of finance, law and governance (Acharya & Subramanian 2009; Acharya & Xu, 2017; Shen & Zhang, 2018).

[12] According to Allen et al. (2015), the hybrid sector includes all non-state and non-listed firms.

that there exist shadow methods for new firms to reduce barriers to entry in China. Djankov et al. (2002) point out that China is a counter-example to most of the literature, which suggests that countries with less democratic and more government control are likely to have onerous regulations of entry for new firms. However, China has much lower entry barriers compared to other countries with similar stages of development. As a result, a surge in private and foreign ownership, and the ownership stake of local governments dramatically increased the intensity of market competition in China's manufacturing sector.[13] According to our data sample, China's average degree of industry competition measured by the Herfindahl–Hirschman Index (HHI) during the sample period from 1998 to 2007 is 98.48%, while the corresponding value in the US during the approximately same period 1997-2008 is only 77.9% (Hoberg et al., 2014). Hashmi (2013) finds that a median value for competitive intensity measured by the Lerner Index (LI) based on a sample of UK firms from 1976 to 2007 is 76%, while the corresponding value for our data sample from 1998 to 2007 is 94.92%. Therefore, given the excessive competition faced by Chinese firms, it is vital to explore the extent to which industry competition affects corporate innovation in China.

To date, most of the studies on the relationship between competition and innovation mainly focus on western developed countries (Blundell et al., 1999; Aghion et al., 2005; Hashmi, 2013) while little is known about China. Will the relationship between competition and innovation in China be different from those in western countries? Answering this question might help develop a better understanding of barriers to China's innovation. Given the

[13] The increased intensity of China's market competition can be reflected by a big rise in the number of corporations. For instance, according to the statistics of the National Bureau Statistics of China (http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A010401&sj=2005), the number of corporate units increased sharply from 6,517,670 in 2010 to 18,097,682 in 2017 and the number of private corporate units increased from 5,126,438 in 2010 to 16,204,143 in 2017.

important role of innovation in shaping growth strategies in emerging markets and the dramatic change in market competition in China, this issue deserves in-depth investigation.

In this study, we focus on a large dataset over the period 1998-2007 compiled by the National Bureau of Statistics (NBS) of China. This sizeable and unbalanced panel of 1,957,772 observations covers 555,124 Chinese firms in all 39 manufacturing, mining, and public utility sectors in 31 provinces (or province-equivalent municipalities). To measure firms' innovation activities, we use the ratio of firms' new product output values to their total assets. To compute the intensity of industry competition we use four measures: the Herfindahl-Hirschman Index (HHI), the Entropy Index (EI), the Lerner Index (LI)/Profit-Cost Margin (PCM), and the natural logarithm of the number of firms (FI). We find that firms' innovation activities are discouraged in sectors where competition becomes more intense. Specifically, our main regressions show that a 10% increase in industry competition reduces the probability that a firm innovates by between 0.12% and 3.49% and reduces innovation output by between 0.03% and 0.92% for innovative firms, depending on which measure of competition we use.

Unlike western developed countries, which are characterized by a well-developed financial system, imperfections in China's capital market might further jeopardize China's rise in innovation by restricting funding on firms' research and development (R&D). In this study, we further exploit two important financial channels through which industry competition deters corporate innovation: industry-level external finance dependence and firm-level financing constraints. We find that the negative effect of competition on innovation is significantly stronger for firms in more externally dependent industries. Furthermore, we find that the moderating effect played by EFD is more pronounced for financially constrained firms: private firms, small firms, young firms, firms without state shares, and firms in the central and western regions. Financially constrained firms rely more on internal finance to fund their innovation activities and exhibit a higher sensitivity of R&D investment to cash flow.

A major challenge in the innovation literature is that innovation is likely endogenous with companies and local market conditions due to reverse causality, omitted variables, and potential measurement errors in empirical research. For example, the firms' decision to enter an industry and invest in innovation could be endogenous and deterred by a high technology gap, and/or the risks and the costs associated with innovation activities. Thus, a correlation between competition and innovation might not prove highly informative about a causal link running from the former to the latter. In the absence of clear identification, the results of prior research are difficult to reach a consensus of the causality. To overcome the endogeneity concerns as mentioned above and gain a clearer understanding of this issue, we improve the identification strategy by exploiting an exogenous shock to competitive intensity. After China's accession into (WTO) in December 2001, the National Development and Reform Commission (NDRC) of China revised its 'Catalog for the Guidance of Foreign Investment Industries' (the Catalog) in 2002 to comply with the WTO regulations (the commitments of industrial openness to foreign investment). The catalogue revision is plausibly exogenous to industry competition by encouraging/restricting foreign investment. In this quasi-natural experiment, we find that in response to the catalogue revision in 2002, firms in sectors where restrictions on foreign investment were lifted (the treatment group) reduced their innovation output more than firms in sectors with unchanged or more restrictions on foreign investment (the control group). This finding confirms our hypothesis according to which more competition (associated with a lifting of restrictions on foreign investment) decreases firms' innovation output. The magnitudes of our difference-in-differences (DID) results suggest that firms in the automobile manufacturing sector (the treatment group) were about 6.64% less likely to innovate than firms in the metal ship manufacturing sector (the control group) from the pre- to post-revision periods. Besides, innovation output for the former was about 3.04% lower than the latter following the exogenous catalogue revision in 2002, which was associated with a shift in industry competitive intensity. Further tests show that the impact is enhanced in industries that are more dependent on external finance.

Still, we further address endogeneity concerns by employing an instrumental variable (IV) approach. We construct a time-varying industry-specific instrument for industry competition and investigate its impact on R&D activities. Specifically, using the number of application procedures that a firm has to go through to enter a particular four-digit sector as the instrumental variable for the intensity of industry competition, we confirm a causal and negative effect of industry competition on innovation activities.[14]

Our results are also robust to the use of various specifications and estimation methods. First, to control for potential measurement errors of innovation, we use the number of firms' patent applications and the ratio of firms' R&D expenditure to their total assets as alternative measures of firms' innovation activities in estimations. Second, to mitigate concerns about omitted factors that may explain firms' innovation activities, we include contemporaneous terms of independent variables in the main regression equations to estimate again. Third, using aggregate industry-level data, we extend our sample period covering from 2001 to 2016 and also find a negative relationship between industry competition and industry-level innovation. Fourth, we re-examine the nonlinearity between competition and innovation in China. We do not find any evidence for the inverted-U relationship as in Aghion et al. (2005). Indeed, China's manufacturing sector is dominated by laggard firms with high competition. Fifth, we break down the national market into eight regional markets classified by the Chinese government in

[14] As defined by the National Bureau of Statistics of China, there are four levels in the China Industry Classification System (GB/T).

estimations to account for the influence of local protectionism. Finally, we find that the results are qualitatively unchanged when we use the random-effects Probit model, measure competitive intensity based on the two-digit or three-digit sector codes, balance our sample data, cluster standard errors by industries rather than firms, use time-series industry-level EFD and firm-level EFD.

Our paper has the contributions as follows. First, our paper contributes to the literature that study industry competition and corporate innovation. The majority of empirical studies find a positive relationship between competition and innovation based on Western developed countries, such as the US context (Schumpeter, 1943; Blundell et al., 1999) and the UK context (Nickell, 1996). Additionally, Aghion et al. (2005) show that there is an inverted-U relationship between competition and innovation in the UK market. Hashmi (2013) re-examines the inverted-U in the US market and finds a significantly negative relationship between competition and innovation, while the magnitude of the relationship is small. He attributes the mildly negative relationship to that US manufacturing firms are technologically less 'neck-and-neck' than their UK counterparts. Unlike prior research, our project adds to this literature by providing empirical support for the 'Schumpeterian effect' ('laggard-and-laggard') that dominates in the largest emerging market economy around the world, namely China.

Second, unlike most of the aforementioned papers, our paper is the first to use a large number of industrial firms which are mainly unlisted to explore the impact of competition on innovation. It is distinct from but also complementary to previous literature, which focuses on listed firms (Blundell et al., 1999; Aghion et al., 2005; Hashmi, 2013). Yet, a relatively small number of listed firms are not representative and are likely to suffer from serious sample selection bias, which may overlook the impact of competition on innovation. Besides, listed firms are less likely to have financing constraints compared to small and medium-sized enterprises (SMEs), which is also neglected by previous studies. Based on a large panel which consists largely of SMEs and unlisted firms (approximately 95%), we provide new evidence that there is a negative relationship between competition and innovation given by the increasingly severe competition that characterizes the fast growth of emerging economies' manufacturing industries. Additionally, we explore the heterogeneous effect of competition on innovation across different firms' characteristics including ownership, size, age, state shares, and location. Such analysis could not only provide researchers microeconomic evidence for the debate on the competition-finance-growth nexus but also can help corporations and policymakers fully understand the economic consequences of competition and finance and then provide more guidance on how to stimulate innovation in an emerging market economy.

Third, the paper also enriches the literature on firm innovation in China. Prior research has been explored various factors in the context of innovation in China, such as institutional ownership (Rong et al., 2017), R&D subsidies (Boeing, 2016), total factor productivity (Boeing et al., 2016), and intellectual property rights protections (Fang, et al., 2017). Our paper, however, suggests that intense competition and capital market imperfections also jeopardize China's rise in innovation. We believe that these are important factors that have been overlooked by prior research.

Fourth, our study contributes to the literature by providing evidence on a link between the real economy and the financial sector and offering insights into the real effects of competition and finance on innovation. For the first time in the Chinese context, we extend the existing research by investigating two important financial channels (industry-level external finance dependence and firm-level financing constraints) through which industry competition deters corporate innovation. Given the significant capital market imperfections characterizing it, China's financial system has limitations to promote economic growth, which could be a challenge to China's innovation. This research contributes to the understanding of China's unconventional growth path. Additionally, our paper complements the literature on how financial conditions affect firms' investment decisions (Fazzari et al., 1988; Rajan & Zingales, 1998).

Fifth, our study provides clear identification of a causal effect of competition on innovation by setting up a quasi-experiment based on a plausibly exogenous shift in industrial openness to foreign investment and using a time-varying industry-specific instrument for industry competition. Based on our empirical findings, we push the causality debate one step further by finding evidence for channels through which competition and finance affect innovation.

The remainder of the paper is structured as follows. In Section 2.2 we develop testable hypotheses. In Section 2.3 we construct our key variables. In Section 2.4 we describe our dataset and report summary statistics. In Section 2.5 we illustrate our model specifications. In Section 2.6 we discuss our main empirical results. In Sections 2.7 and 2.8 we show further robustness tests and extensions. In Section 2.9 we conclude.

2.2. Developing hypotheses

In this section, we develop three testable hypotheses based on economic theories and empirical findings. First, we examine whether there is a relationship between industry competition and firms' innovation activities in China. As industry competition increases, do firms' innovation activities decrease or increase? Second, we test the extent to which industry external finance dependence affects the relationship between competition and innovation.

Third, we study whether firms' financing constraints influence the effect of competition on their innovation activities in China.

2.2.1. General industry competition hypothesis

Over 40 years of economic reform and rapid expansion of a market economy in China, there has been a tremendous surge in the number of corporations (especially a "Hybrid Sector") aggressively competing for profits because of lower entry barriers for new firms (Allen et al., 2015). Therefore, the Chinese market has been characterized by intense competition (Wu, 2012). According to the 'Schumpeterian effect,' excessive competition decreases firms' short-term profits from catching up with the leader, which imposes short-term pressure on managers and negatively affects the internal finance available for innovation investment. Due to short-termism and myopic investment behaviour (Bushee, 1998), firms in competitive industries prefer investments that can generate short-term earnings to long-term and uncertain investments such as R&D activities (Aghion et al., 2013). Furthermore, according to Bernanke and Gertler (1989), a decrease in the short-run profits reduces firms' value, e.g., net asset value. Net asset value is inversely related to the external finance premium that firms face since net assets are perceived as collateral to guarantee future loan payments. Thus, when market competition becomes intense firms may have to forego long-term innovation investment as managers have to face higher costs of external financing (Holmstrom, 1989; Brown et al., 2009). Firms in competitive industries, e.g., in the manufacturing sector, have to innovate less because of a lack of internal and external capital available for their R&D investments. We, therefore, hypothesize as follows:

Hypothesis 1: *Industry competition is negatively related to firms' innovation activities in China.*

2.2.2. Industry external finance dependence hypothesis

According to Hypothesis 1, severe competition in China's market adversely affects both internal and external finance for firms' innovation activities. Such an impact could differ for firms with different needs for external finance. Firms in industries with higher EFD may become more vulnerable for two reasons. First, these firms have insufficient internal capital and rely more on external capital to fund their R&D activities. These firms tend to have higher gearing ratios because of their large demand for external finance, even if they face a higher premium of external finance caused by increased competition. According to the trade-off theory, higher gearing ratios can lead to high potential bankruptcy and monitoring risks, which undermines these firms' value and further increases their borrowing costs of external funds (Myers, 1984; Myers & Majluf, 1984; Campbell & Kelly, 1994). Additionally, banks may impose pressure on firms with higher gearing ratios, which limits corporate innovation. Second, R&D investment opportunities in industries with higher EFD are accompanied by sparse information (Hsu et al., 2014). It is more difficult for banks to evaluate these firms' innovative projects due to information problems. This accompanied by insufficient internal capital to service debt (Brown et al. 2012) means that banks might refuse to finance innovation investments of firms in industries with higher EFD. Consequently, as industry competition increases, firms in industries with higher EFD have to reduce investment in long-term and uncertain projects such as R&D. In contrast, firms in industries with lower EFD suffer less since they do not rely more on external capital. The financial advantage of depending on internal capital for firms in industries with lower EFD can alleviate the negative effect of higher external finance premiums caused by increased competition. Therefore, we put forward our second hypothesis as follows:

Hypothesis 2: *The negative effect of competition on innovation increases with the degree of dependence on external finance.*

2.2.3. Firms' financing constraints hypothesis

In principle, firms can choose to finance R&D investment using either internal or external finance. Yet, when they are financially constrained, they might not be able to obtain credit for investments in innovation. Specifically, financing constraints can cause information asymmetries that are associated with innovation and impose financial pressure on firms' managers when it comes to R&D investments. As competition increases, short-termism and cost premiums may force financially constrained firms to reduce their R&D investments. To smooth R&D investments, R&D-intensive firms with financing constraints may have to rely more on their limited internal finance than on external finance, making R&D investment sensitive to cash flow. For instance, Lyandres and Palazzo (2016) emphasize the importance of financing constraints in explaining the relation between innovative firms' cash holdings and the expected intensity of competition. In contrast, financially healthier firms might have better access to bank loans or other forms of external finance for R&D investments. This financing advantage can alleviate the negative impact of increased competition on innovation. Consequently, financially healthier firms in competitive EFD industries can innovate more than financially constrained firms. Therefore, we propose our third hypothesis as follows:

Hypothesis 3: *Financing constraints will tighten the negative impact of competition on innovation in industries with greater EFD.*

2.3. Variable measures

2.3.1. Measuring innovation

In this study, we define a firm's innovation activities as the ratio of new product output values to total assets.[15] Compared to R&D expenditure, new product output value has two advantages. First, it is believed to be a better measure of innovation output and the level of efficiency of innovation activities compared to R&D expenditure, which is merely a measure of innovation input (Criscuolo et al., 2010). Second, data on R&D expenditure in the sample dataset is only available from 2001 to 2007, while data on new product output value is available from 1998 to 2007.[16] However, we also use the ratio of R&D expenditure to total assets and the number of patent applications for robustness tests.[17]

2.3.2. Measuring competition

In this study, we construct four measures of industry competitive intensity: the Herfindahl-Hirschman Index (HHI), the Entropy Index (EI), the Lerner Index (LI)/Profit-Cost

[15] In the *China Statistical Yearbook* (2006), new products are defined as "those new to the Chinese market which either adopt completely new significant principles, technologies or designs, or are substantially improved in comparison with existing products in terms of performance and functionality, through significant changes in structure, materials, design or manufacturing process."

[16] Data on both new product output values and R&D expenditure are missing for 2004. The results remain qualitatively unchanged if we use the average of the values in 2003 and 2005 to impute for these missing data.

[17] Patent applications might not fully reflect the development level of firms' innovation output in China because of the two reasons. First, due to the relatively weak intellectual property rights (IPRs) protection in China and the relatively long, complicated, and expensive patenting process, many SMEs might decide not to apply for patents to cut costs. Therefore, the percentage of firms filing patent applications is lower (3.24% for our data sample) than the percentage of firms with a positive new product output value (6.63% for our data sample). Second, the share of invention patents is low (26.52%) compared to those of design patents and utility model patents, although the former is better to proxy innovation with novelty.

Margin (PCM) and the natural logarithm of the number of firms (FI). These four measures are based on GB/T four-digit sector codes.

2.3.2.1. Herfindahl-Hirschman Index (HHI)

Our first measure of industry competition is the Herfindahl-Hirschman Index (HHI), which is well-grounded in industrial organization theory, competition law, and antitrust and technology management. Specifically, following Nickell (1996) and Cai and Liu (2009), we compute the competitive intensity in industry j by using one minus the sum of the squares of all firms' market shares in the industry. We define the HHI industry competitive intensity as follows:

$$Competition_{j,t}\ [HHI] = 1 - \sum_{i=1,i\in j}^{Nj} S_{i.j,t}^{2} = 1 - \sum_{i=1,i\in j}^{Nj} (\frac{X_{i,j,t}}{X_{j,t}})^{2} \quad (2.1)$$

where subscript i indexes firms, j industries, and t years (t = 1998-2007). Thus, $S_{i,j,t}$ is the market share of firm i in industry j in year t. Market shares are computed based on firms' main business product sales (Cornaggia et al., 2015).[18] $X_{i,j,t}$ represents the value of the main business product sales of firm i in industry j in year t, and $X_{j,t}$ represents the main business product sales of all firms in industry j in year t. To build a positive indicator of industry competition, we subtract the industry HHI from one. Thus, the HHI index industry competition ($Competition_{j,t}\ [HHI]$) takes a value between 0 and 1. 0 suggests perfect monopoly (no competition) and 1 indicates perfect competition (no monopoly). A higher value of $Competition_{j,t}\ [HHI]$ represents a higher degree of industry competition.

[18] We also use firms' total assets to calculate their market shares (Giroud & Mueller, 2010) for a robustness test. The estimation results are not reported for brevity but remain qualitatively unchanged.

2.3.2.2. Entropy Index (EI)

Our second measure of industry competition is the Entropy index (EI). Like the HHI, the EI is also computed by using firms' market shares. Compared to the HHI, the EI has three unique features. First, it gives more weight to small businesses, and so it sensitively reflects the influence of changes in small-scale enterprises in the market. By contrast, the HHI is more influenced by large firms (Haushalter et al., 2007). Second, the HHI is an inverse indicator of industry competitive intensity, while an industry with a higher value of the EI can be understood to be more highly competitive. Third, the distribution range of the HHI is from 0 to 1, while the EI has no numerical distribution limit. The EI industry competitive intensity is calculated as:

$$Competition_{j,t}\ [EI] = log(\tfrac{1}{E})_{j,t} = \sum_{i=1, i\in j}^{N_j} X_{i,j,t}\ [log(\tfrac{1}{X_{i,j,t}})] \qquad (2.2)$$

2.3.2.3. Lerner Index (LI) or Profit-Cost Margin (PCM)

Our third measure of industry competition is the Lerner Index (LI) or the Profit-Cost Margin (PCM). A firm's LI is defined as its product's price minus its marginal costs and then divided by the price (Nickell, 1996; Aghion et al., 2005). Following Cai and Liu (2009) and Peress (2010), we use the ratio of main operation profits to main operation sales (Profit-Cost Margin – PCM) to construct the firm-level $LI\ (PCM)_{i,j,t}$:

$$LI\ (PCM)_{i,j,t} = \frac{Main\ Operation\ Profits}{Main\ Operation\ Sales} = \frac{Main\ Operation\ Sales - Main\ Operation\ Costs}{Main\ Operation\ Sales} \qquad (2.3)$$

To account for the impact of firm size, we subsequently compute the industry-level LI (PCM) from the value-weighted (based on market share) average LI (PCM) across firms in an industry (Peress, 2010). A higher level of an industry's LI (PCM) indicates that it has stronger market power or a higher concentration ratio (a weaker degree of competition). As with the

HHI, to build a positive indicator of industry competitive intensity, we use one minus the industry-level LI (PCM) to construct the $LI\ (PCM)$ industry competitive intensity as:[19]

$$Competition_{j,t}\ [LI\ (PCM)] = 1\ - \sum_{i=1,i\in j}^{N_j} [S_{i,j,t}\ *\ LI\ (PCM)_{i,j,t}] \tag{2.4}$$

2.3.2.4. Natural logarithm of the number of firms (FI)

Our fourth measure of industry competition is based on the number of firms in an industry (Dixit & Stiglitz, 1977; Cai & Liu, 2009). Specifically, we use the natural logarithm of the number of firms to measure the FI industry competitive intensity as:

$$Competition_{j,t}\ [FI] = \log\,(N_{j,t}) \tag{2.5}$$

Where $N_{j,t}$ is the number of all firms in industry j in year t. Like the EI, the FI also has no absolute numerical limit. A higher value of $Competition_{j,t}\ [FI]$ means higher industry competitive intensity.

2.3.3. Measuring industry external finance dependence (EFD)

Firms in an industry with higher EFD rely more on external funds to finance the tangible and intangible investments they desire, including innovation activities. Previous studies show that the degree of external finance dependence varies across industries (Rajan & Zingales, 1998). For example, industries such as electrical machinery are more externally dependent, while industries such as tobacco have fewer needs for external funds. To construct industry j's dependence on external finance (EFD), following Rajan and Zingales (1998), we first compute

[19] To assess the robustness of our empirical results, we also divide 1 by the number of firms in an industry and then multiply the sum of the LI (PCM) of all firms in the industry to get an equally weighted concentration ratio. We subsequently subtract this ratio from 1 to obtain the value of industry competitive intensity (Aghion et al., 2005). The results are qualitatively the same as those of value-weighted indexes.

each firm's external finance dependence as the fraction of its capital expenditure that is not financed through its internal cash flow.[20] Next, we construct the median value of the external finance dependence for all the firms in industry j in year t to create a time series of industry j's external finance dependence. Finally, we measure industry j's dependence on external finance ($Dependence_j$) as the median value of its time series of external finance dependence over the period 1998-2007. Like the measures of industry competitive intensity, the calculation of industry level of external finance dependence is also based on GB/T four-digit sector codes.

2.3.4. Measuring financing constraints

According to the financial constraints hypothesis proposed by Fazzari et al. (1988), the high sensitivity of investment to internal funds can be seen as a measure of financing constraints. In their influential paper, Fazzari et al. (1988) find that cash flow has a stronger impact on investments by low-dividend firms than that by high-dividend firms. They interpret this fact as supporting the financing constraints hypothesis since firms that pay low dividends are typically smaller and younger, and it is generally difficult or expensive for these firms to obtain external financing. Therefore, if cash flow declines for these firms, the investments will go down as well. In addition to investigating the link between financing constraints and fixed investment, many scholars also extend this method to test for the presence of financial constraints on firms' innovation activities (Brown et al., 2012; Guariglia & Liu, 2014). According to this view, R&D investments tend to be constrained by the availability of internal finance due to limited collateral and uncertain risk characterizing innovation. Therefore, to test Hypotheses 3 about financial constraints, we use the sensitivity of innovation to cash flow to

[20] Following Acharya and Xu (2017), we also include R&D expenditure as part of capital expenditure to compute an industry's dependence on external finance for a robustness test. The results (not reported) are qualitatively the same as our main findings.

measure the degree of financial constraints faced by firms' innovation activities. Besides, we separate firms into different groups based on their a priori likelihood of facing financial constraints in the Chinese context.

First, we differentiate firms through ownership types. We compare state-owned enterprises (SOEs) and private firms since the latter is subject to more financial constraints than the former. It could be interpreted as follows. First, in China, the government has much control over the allocation of financial resources. Therefore, SOEs can enjoy a preferential status when seeking bank loans and other key inputs (Guariglia & Yang, 2016). Second, *guanxi* (political affiliation) is a central idea in every aspect of Chinese society.[21] Compared to private firms, SOEs are more likely to benefit from *guanxi,* such as by obtaining tax incentives for innovation spending and direct grants, which provides them with more funds to innovate (Guariglia & Mateut, 2016). Third, banks in China are mainly controlled by state capital, which causes a 'lending bias' and 'institutional discrimination'. Since the late 1990s, the Chinese government has used bank credit as a political instrument to support SOEs, which thus absorbs three-quarters of bank lending and crowd out private firms' access to formal bank loans. Therefore, in China, given the unique state-dominated financial system, SOEs can gain more financing advantages over their private counterparts. Huang (2003) describes this phenomenon as a 'political pecking order' in China. Compared to SOEs, private firms generally face more financial constraints.

Second, we measure financing constraints by using firms' size and age. Size and age have been commonly used as proxies for financing constraints on R&D investments. First, small and young firms are typically characterized by high idiosyncratic risk and high

[21] *Guanxi* means a web of connections in personal or business relations and describes the fundamental dynamic in personalized networks of influence. As a crucial informal governance mechanism, *guanxi* allows firms to make more profits.

bankruptcy costs, which makes their access to external finance costlier (Guariglia & Yang, 2016). Second, compared to large and mature firms that enjoy the benefits of economies of scale, small and young firms do not have enough physical assets to use as collateral or a sufficiently long track record (Coad et al., 2016). Therefore, small and young firms are more vulnerable to information asymmetry and not only systematically discriminated by the state-owned banks but also by other types of formal financing (Ayyagari et al., 2010).

Third, we measure financing constraints by using firms' state shares. Firms with more state shares are more likely to have connections with governments. For this reason, it is easier for these firms with high political affiliation to obtain credit from state-owned banks (Khwaja & Mian, 2005; Guariglia et al., 2011). Therefore, firms without state shares are more likely to face financing constraints than firms with state shares.

Last, we investigate this issue by using firms' locations, as China's regional financial development level is largely unbalanced. Since China's coastal regions are more financially developed than China's central and western regions, firms in coastal regions can benefit by easily obtaining more bank loans and facing fewer financial constraints than ones in central and western regions (World Bank, 2006).

2.4. Data and summary statistics

2.4.1. Data

This study uses firm-level production data drawn from the annual accounting reports collected and compiled by China's National Bureau of Statistics (NBS) covering the period 1998-2007.[22] The census dataset provides financial information on all 'above-scale' Chinese

[22] The data up to 2007 are more widely used in research (Guariglia et al., 2011; Brandt et al., 2012; Liu & Qiu, 2016). The reasons why we only use the data until 2007 are as follows. First, there are some key variables missing

industrial enterprises with all types of ownership. The criterion for inclusion in the dataset is an annual total main business income (i.e., sales) of more than five million Chinese yuan (CNY), nearly 750,000 US dollars. The NBS dataset designates each firm with a legal identifier known as the legal person code, which can be used to construct a panel. Approximately 95% of the firms in the dataset are unlisted firms, and public firms only account for about 5%.[23] There are four advantages of using the microeconomic-level data provided by this database. First, aggregation problems in estimation results can be eliminated. Second, accounting of national income from these firms is done by the central NBS, which is advantageous as it can avoid potential manipulation by local authorities. Third, we can take firm heterogeneity into account using this very large sample of firms. Fourth, the dataset covers more than 90% of all Chinese industrial firms' sales, which can provide a better measure of the degree of industry competition in China than the data only on listed firms.

The original sample contains 2,222,061 observations. To minimize the potential influence of outliers, we process the data as follows. First, in 2002 the Chinese central government revised its industry classification following the 2001 WTO regulations.[24] Following the new classification, we match the industry codes and exclude those that disappeared or transferred to other non-manufacturing sectors after 2002.[25] The firms in the

---

after 2007. For example, the current-year depreciation is missing from 2008 to 2010 while we need this to calculate the corresponding values for cash flow. Second, the threshold for inclusion of 'above-scale' enterprises is changed by China's NBS in 2011 from annual sales of more than 5 million to more than 20 million Chinese yuan. Third, the financial crisis in the period 2008-2010 could also lead to a potential estimation bias if we add the data of this three years.

[23] The NBS dataset does not allow us to separate listed firms from unlisted ones.

[24] For example, some industries are broken down into different industries, while others are merged. A description of the 2002 industry classification is available: http://www.stats.gov.cn/tjgz/tjdt/200207/t20020711_16330.html.

[25] For example, the 'logging operation industry' with two-digit code '12' was moved out of mining industries after the year 2002. However, the proportion of disappeared or transferred industries is quite low (only approximately 0.17% of the sample).

final sample operate in 39 GB/T two-digit manufacturing, mining, or public utility sectors and across all 31 Chinese provinces or province-equivalent municipal cities.[26] Second, following Cai and Liu (2009), we delete observations of firms whose main business income is below five million Chinese yuan to fit the criterion of 'above-scale,' which constitute around 11.0% of the sample.[27] Third, we drop observations with negative values of sales, total assets minus total fixed assets, total assets minus liquid assets, total sales and accumulated depreciation minus current depreciation, and also observations without a record of the industry code, ownership type or location information, which constitute approximately 0.90%. Fourth, we trim observations in the one per cent tails of each of firm-level continuous variables in our main regressions to mitigate the potential influence of outliers.[28] These processes lead to a final unbalanced panel of 1,957,772 firm-level observations covering 555,124 Chinese firms between 1998 and 2007.[29] All the variables are deflated using the provincial-level gross domestic product (GDP) deflators produced by the Chinese NBS.[30]

Fig. 2.1 shows time series plots of the mean innovation rates and the average competitive intensity measured by the HHI based on GB/T four-digit sector codes over the period from 1998 to 2007.[31] First, we find that the innovation rate for the full sample is

---

[26] Our data sample does not include firms in Hong Kong, Macao, or Taiwan.

[27] After 1998, the dataset records non-SOEs with annual sales of more than five million Chinese yuan (all 'above-scale' non-SOEs) and all SOEs. In other words, SOEs that are not 'above-scale' are also included.

[28] For new product output value and R&D expenditure, we only trim the tail at 99% because these variables are left-censored at zero. Since the number of patent applications is a discrete variable and the share of firms having patent applications is quite low (3.24%), we do not trim the number of firms' patent applications.

[29] Appendix A shows details of the structure of the unbalanced panel.

[30] See Appendix D for the complete definitions of all the variables in this study. All variables (except tangible fixed assets) are deflated using the provincial ex-factory producer price indices (a price deflator for fixed capital formation), which is obtained from the National Bureau of Statistics (NBS) of China. Information on the province-level GDP deflators can be viewed on the NBS website (http://data.stats.gov.cn/).

[31] The innovation rate is defined as the percentage of firms which have a positive new product output value. The rate for 2004 cannot be calculated since there is no record of new product output value for that year.

relatively low (an average value of 8.69%). Specifically, it drops from approximately 8.80% in 1998 to 6.68% in 2003, increases to 10.0% in 2006 and again decreases to 8.54% in 2007.[32] Second, we find that there is an increasing trend in industry competitive intensity from 1998 to 2007. Specifically, China's average competitive intensity slightly declines from 1998 to 2000, which may have been caused by the 1997 Asian economic crisis, and then starts to increase, especially after 2002, which is possibly explained by China's accession into the WTO in late 2001. Third, we also find that there is an approximately negative relationship between the innovation rate and average competitive intensity, which is consistent with Hypothesis 1.

[*Insert Fig. 2.1 here*]

Next, we find that innovation rates vary substantially between SOEs and private firms. SOEs have higher innovation rates than private firms over the whole sample period. A possible reason for this is that the former enjoy the privilege of cheap bank loans for innovation input. However, we find that private firms have an increasing trend in their innovation rates during the sample period, especially after 2003, which may be explained by the rapid growth of Chinese private firms with more enthusiasm for innovation. In contrast, SOEs show a downward trend in their innovation rates. Therefore, the difference in mean innovation rates between SOEs and private firms declines from around 10.93% in 1998 to 3.20% in 2007.

Fig. 2.2 shows snapshots of the annual innovation rates across different Chinese prefecture-level administrative divisions in 1998 and 2007. First, it shows that administrative divisions in the central and western regions have higher innovation participation rates.[33] This

[32] The Dotcom bubble in the late 1990s and the 2007 financial crisis may account for the decrease in innovation, and the implementation of government innovation incentive policies in 2003 may explain the short recovery after 2003.

[33] See Appendix D for details of the region classification and Appendix C for details of the prefecture-level innovation distribution in 1998 and 2007.

finding is contrary to the conventional view that firms in the eastern regions are more likely to innovate. However, the finding is consistent with Hypothesis 1 that more competition discourages firms' innovation activities since the firms in the coastal regions are exposed to tougher competition than those located in the central and western regions. Second, we also find that innovation rates in most administrative divisions decrease from 1998 to 2007. As Fig. 2.2 shows, there are 217 prefecture-level administrative divisions, showing decreasing innovation rates during this period and only 114 prefecture-level administrative divisions with increased rates. This finding is also consistent with Hypothesis 1 that there is a negative relationship between competition and innovation since the reduction in innovation rates may be explained by an upward trend in industry competitive intensity in China from 1998 to 2007.

[*Insert Fig. 2.2 here*]

Fig. 2.3 presents a plot of annual innovation rates against the four different measures of industry competitive intensity based on GB/T four-digit sector codes. We find that there is a notable decreasing tendency in innovation rates as competition increases. There is a significant and negative association between innovation rates and competition at the 1% level, regardless of the measure of competition.[34] The finding is in line with Hypothesis 1, according to which innovation drops with an increase in competition.

[*Insert Fig. 2.3 here*]

[34] We also find a significantly negative relationship between innovation rates and competitive intensity based on GB/T two-digit codes and three-digit codes, which is not reported for brevity. See Appendix B for details of mean innovation rates and competitive intensity across GB/T Two-digit industries.

2.4.2. Summary statistics

Table 2.1 provides descriptive statistics (sample means and medians) of the main variables for the full sample, firms with/without innovation activities (with/without positive new product output values), SOEs, and private firms.[35] The number of observations of innovative firms (60,255) is around one-tenth that of non-innovative firms (633,493), which suggests a low level of innovation participation for firms in China. Besides, there are 260,919 private firm-year observations compared to 66,978 SOE firm-year observations.

[*Insert Table 2.1 here*]

It is clear that firms with positive new product output values have a greater number of patent applications and a higher ratio of R&D expenditure to total assets. Non-innovative firms face stiffer competition than innovative firms regardless of the measure of industry competition. Specifically, the four measures of industry competition for firms without innovation output are HHI 98.52%, EI 5.81, LI (PCM) 94.95% and FI 6.89, which are significantly greater than the levels for firms with innovation output [HHI 98.05%, EI 5.46, LI (PCM) 94.64% and FI 6.60]. This finding is in line with Hypothesis 1. The lower values of industry external finance dependence and the cash flow to total assets ratio for innovative firms (averages of 57.13% and 7.91%, respectively) may be explained by the fact that innovative firms in China spend more internal finance and rely less on external finance to support their capital expenditure.

For the different measures of financial constraints, we observe that innovative firms generally are larger (with average total assets of 365.13 million yuan), more mature (with an average age of 17.52 years) and have a greater percentage of state shares (16.46%) than non-

[35] We summarize the number of observations estimated into regressions. This is the reason that the number of total observations is 693,748 in Table 2.1 for 289,738 firms. If we summarize the number of all observations in the panel (1,957,772) for 555,124 firms, the findings keep qualitatively consistent.

innovative firms (whose corresponding figures are 83.68 million yuan, 11.70 years and 9.08%). These differences can be partly explained by the fact that large firms, mature firms, and firms with more state shares tend to face fewer financial constraints and so have more resources to invest in innovation. Our findings are consistent with Ayyagari et al. (2011) that large and mature firms with sufficient resources invest more in innovation that is long-term and has high uncertainty.

In Table 2.1, we also show the differences between SOEs and private firms. Generally, private firms have a higher ratio of new product output value (2.89%) and a lower ratio of R&D expenditure to total assets (0.09%) compared to SOEs, for which the corresponding values are 2.68% and 0.11%, respectively. This finding shows that SOEs have a relatively lower innovation input-output efficiency compared to private firms. The statistic that the number of private firms' patent applications (0.026) is lower than that of SOEs (0.037) may be explained by that the patenting process is long and, which might discourage relatively small private firms from patenting their innovation. For the different measures of industry competition, we find that private firms are more likely to operate in industries with more competitive intensity while SOEs tend to operate in less competitive industries. Regarding industry external finance dependence, SOEs have higher EFD (65.24%) than private firms (58.46%), which suggests that SOEs rely more on external funds to finance their investments. This is possibly due to their privilege of being able to obtain cheap loans from state-owned banks.

2.5. Model specifications and estimation methodology

2.5.1. Baseline model specification

To test the impact of industry competition on firms' innovation activities, following Bond and Meghir (1994), Bond et al. (2003), Brown et al. (2009), we estimate a dynamic Euler equation model.[36] The structural model "captures the influence of current expectations of future profitability on current investment decisions" (Bond et al., 2003), which is less likely to be biased by the misspecification due to investment opportunities not properly accounted for in investment regressions. We denote a firm's new product output values to total assets ratio as $np_{i,j,t}$, its sales to total assets ratio as $s_{i,j,t}$, its cash flow to total assets ratio as $cf_{i,j,t}$ and its ratio of new long-term debt to total assets as $dbt_{i,j,t}$.[37] $Competition_{j,t}$ represents industry competitive intensity. The equation regressed is:

$$np_{i,j,t} = \beta_1 np_{i,j,t-1} + \beta_2 np^2_{i,j,t-1} + \beta_3 s_{i,j,t-1} + \beta_4 cf_{i,j,t-1} + \beta_5 dbt_{i,j,t-1} + \beta_6 Competition_{j,t-1} + V_i + V_t + V_o + V_j + V_r + e_{i,j,t} \ , \tag{2.6}$$

where the subscript *i* indexes firms, *j* industries, *o* ownership, *r* region and *t* time (where *t* = 1998-2007). The error terms in Eq. (2.6) are made up of six components. V_i is a firm fixed effect. V_t is a year fixed effect, which we control by including year dummies capturing time-varying movements in the aggregate interest cost and the business cycle. V_o is a set of five dummy variables to control for firm ownership status, with an SOE dummy being the benchmark (Cai & Liu, 2009).[38] To capture the industry effect and the location effect, we also

[36] This Euler equation model is a modified version of the fixed investment specification used by Whited (1992) and Bond et al. (2003).

[37] New long-term debt is the difference between long-term debt in the current year and the previous year.

[38] Firm ownership categories are defined according to the majority (at least 50%) of a firm's total capital paid in by six different types of agents. Specifically, we partition our firms into state-owned enterprises (SOEs); foreign

construct an industry-specific component (V_j)[39] and a location-specific component (V_r)[40]. Finally, $e_{i,j,t}$ is an idiosyncratic error term.

According to Hypothesis 1, the marginal effect of industry competitive intensity (β_6) should be negative. A significant and negative β_6 suggests that industry competition will discourage innovation. As regards the other variables, the structural model implies that the marginal effect of β_1 should be positive, and under the assumption of quadratic adjustment costs in the Euler equation, the marginal effect of β_2 should be negative. The marginal effect of the lagged sales-to-total assets ratio (β_3) should be negative under perfect competition.[41] Besides, under the assumption that cash flow does not pick up investment opportunities, if there is an indicator of the presence of internal financing constraints β_4 should be positive (Fazzari et al., 1988). Specifically, β_4 should be greater for firms facing more financial constraints than for firms facing fewer financial constraints. β_5 should be insignificant, or its magnitude should be lower than that of cash flow because firms prefer internal finance to external finance.

---

firms; Hong Kong, Macao & Taiwan firms (HMT firms); private firms; collective firms; and mixed-ownership firms.

[39] We use GB/T two-digit sector codes rather than four-digit sector codes as industry dummy variables to control for industry fixed effects. This is because of the limitation of statistical software packages when we estimate a random-effects Tobit model for such a large sample of approximately 700,000 observations. However, we find the results are quantitatively similar and qualitatively consistent if we use a pooled Tobit estimator based on the three-digit and four-digit sector codes.

[40] The location dummy variables are based on eight economic regions administered by the State Council of China: Northern Coastal (Shandong, Hebei, Beijing, and Tianjin), Southern Coastal (Guangdong, Fujian, and Hainan), Eastern Coastal (Shanghai, Jiangsu, and Zhejiang), North Eastern (Liaoning, Heilongjiang, and Jilin), Mid-Yangtze Range (Hunan, Hubei, Jiangxi, and Anhui), Mid-Huanghe Range (Shaanxi, Henan, Shanxi and Inner Mongolia), South Western (Guangxi, Yunnan, Sichuan, Chongqing, and Guizhou) and North Western (Gansu, Qinghai, Ningxia, Tibet, and Xinjiang).

[41] Our results are robust to using sales growth instead of the sales-to-total assets ratio to proxy for investment opportunities.

2.5.2. Specification with industry external finance dependence (EFD)

To test Hypothesis 2, following Hsu et al. (2014) and Acharya and Xu (2017), we augment Eq. (2.6) by including the interaction term between the industry EFD variable ($Dependence_j$) and the competition variable ($Competition_{j,t-1}$) to get Eq. (2.7) as follows:[42]

$$np_{i,j,t} = \beta_1 np_{i,j,t-1} + \beta_2 np_{i,j,t-1}^2 + \beta_3 s_{i,j,t-1} + \beta_4 cf_{i,j,t-1} + \beta_5 dbt_{i,j,t-1} +$$

$$\beta_6 Competition_{j,t-1} + \beta_7 Competition_{j,t-1} * Dependence_j +$$

$$\beta_8 Dependence_j + V_i + V_t + V_o + V_j + V_r + e_{i,j,t} \qquad (2.7)$$

In accordance with Hypothesis 2, the marginal effect of β_7 should be significant and negative. A significant and negative β_7 suggests that the negative effect of competition on innovation increases with the degree of dependence on external finance. We expect that increased industry competition can discourage firms' innovation activities more in industries with higher EFD because these firms' demand for external capital cannot be satisfied.

2.5.3. Estimation methodology

One significant feature of the data is that a large number of firms do not have a positive new product output value. Thus the dependent variable in our study is censored at zero. To consider this censored distribution and yield consistent results, we use the Tobit estimator and report marginal effects (percentage change effects) rather than coefficients. Positive marginal effects suggest an increase in the probability that a firm will innovate and an increase in the

[42] Theoretically, if we control for an industry effect (V_j) we cannot include the single term of the EFD variable ($Dependence_j$) in Eq. (2.7) because otherwise, it would cause a collinearity bias. However, since we choose the GB/T two-digit sector codes instead of the GB/T four-digit sector codes as industry dummy variables, we can have the single term ($Dependence_j$) in our regressions.

new product output value. There are three types of marginal effects in the Tobit model.[43] Because the sign and significance of the three types of marginal effects are all consistent, we only report marginal effects in the quantity of truncated data to show the effect of a unit change in industry competition on innovation for firms with a positive new product output value. Furthermore, to account for firm heterogeneity, we use the random-effects Tobit estimator in the regressions to remove any unobserved heterogeneity at the firm level. Standard errors are also robust to heteroscedasticity, and we cluster them at the firm level.[44]

2.6. Empirical results

2.6.1. Competition and innovation

To test Hypothesis 1, columns (1) to (4) in Table 2.2 show the estimation results using the baseline Eq. (2.6) with the random-effects Tobit estimator. Columns (1) to (4) correspond to the different measures of industry competition, i.e., the HHI, the EI, the LI (PCM) and, the FI. We find that the marginal effects (quantity effects) associated with the variable ($Competition_{j,t-1}$) are all negative [HHI -9.157%, EI -0.322%, LI (PCM) -4.952% and FI -0.266%] and significant at the 1% level, regardless of which measure of industry competition is used. These results suggest that an increase in industry competition decreases firms' new

[43] The first is a probability effect that is the marginal effect of the explanatory variables on the probability that a firm will have a positive new product output value. The second is a quantity effect that is the marginal effect of the independent variables on a firm's expected new product output value, given that the observations are truncated, which excludes the observations without a positive new product output value. The third is a quantity effect that is the marginal effect of the independent variables on a firm's expected new product output value, given that the observations are censored, which include all observations with/without a positive new product output value.

[44] We also use the Pooled Tobit estimator for a robustness test, and the results are consistent with our main empirical findings. For brevity, we do not report them.

product output values. To be precise, a 1% increase in $Competition_{j,t-1}$ is associated with a decrease of 0.092% (HHI), 0.003% (EI), 0.050% (LI) and 0.003% (FI) in $np_{i,j,t}$ for innovative firms. As regards the probability effects (not reported), an increase in industry competition significantly decreases the probability that a firm innovates. Specifically, a 1% increase in industry competition leads to a decrease of 0.349% (HHI), 0.014% (EI), 0.319% (LI), and 0.012% (FI) in the probability that a firm will have a positive new product output value. These results confirm Hypothesis 1, according to which increased competition in Chinese manufacturing sectors has a 'Schumpeterian effect' that leads to a reduction in firms' innovation activities.

[*Insert Table 2.2 here*]

Our results show that the marginal effects associated with $cf_{i,j,t-1}$ are significantly positive at the 1% level. Specifically, the marginal effect of $cf_{i,j,t-1}$ is 1.934%, 1.929%, 1.869%, and 1.927% in columns (1) to (4), respectively, suggesting that Chinese firms' innovation outputs are constrained by the availability of internal cash flow. This finding reveals that Chinese firms rely significantly on internal capital to smooth innovation, given the limited collateral value and the high uncertainty risk characterizing innovation.

For the other control variables, we observe that the marginal effects of $np_{i,j,t-1}$ are significantly positive at the 1% level. The magnitudes of the marginal effects are close to 50%, reflecting the persistence of Chinese firms' innovation activities given the long-term cycle and high adjustment costs of innovation. The marginal effects associated with $np^2_{i,j,t-1}$ are significantly negative at the 1% level, remaining consistent with the theoretical equation. The negative signs of the marginal effects of $s_{i,j,t-1}$ show that Chinese firms are less likely to innovate as their market shares expand. This finding may indicate that Chinese firms have short-sighted behaviour. Next, the marginal effects of $dbt_{i,j,t-1}$ are poorly determined, showing that long-term debt is not a preferred financial channel for Chinese firms' innovation activities.

2.6.2. Industry external finance dependence

To test Hypothesis 2, columns (5) to (8) of Table 2.2 present the random-effects Tobit estimates of Eq. (2.7), which includes the interaction term ($Competition_{j,t-1} * Dependence_j$). Regardless of the measure of industry competition, we observe that the estimated marginal effects of the interaction term are significantly negative: HHI -2.487%, EI -0.474%, LI (PCM) -2.241%, and FI -0.437%. These results mean that $Dependence_j$ increases the negative impact of $Competition_{j,t-1}$ on $np_{i,j,t}$. Specifically, a rise of one standard deviation in $Dependence_j$ is associated with an increase of HHI 0.313%, EI 0.060%, LI (PCM) 0.281%, and FI 0.055% in the negative marginal effect of $Competition_{j,t-1}$ on $np_{i,j,t}$.[45] Alternatively, for competition measured by the HHI, if the value of EFD increases from its 25th percentile (47.9%) to its 75th percentile (69.0%), the marginal effect of $Competition_{j,t-1}$ on $np_{i,j,t}$ increases by 0.525% [=2.487% * (69.0% - 47.9%)].[46] The estimation results support Hypothesis 2 according to which an increase in industry competition restrains innovation activities more in industries with higher EFD. Additionally, we find that the marginal effects of the single term $Competition_{j,t-1}$ become less significant, which is not particularly

[45] For example, if industry competitive intensity is measured with the HHI, when $Dependence_j$ increases by one standard deviation (12.6%), the negative marginal effect of $Competition_{j,t-1}$ on $np_{i,j,t}$ rises by 0.313% (=12.6% * 2.487%).

[46] As regards to probability effects (not reported), marginal effects of the interaction term are also significantly negative: HHI -4.061%, EI -0.772%, LI (PCM) -3.662%, and FI -0.710%, suggesting that $Dependence_j$ increases the negative effect of competition on the probability that a firm will innovate.

interesting given that the main effect of $Competition_{j,t-1}$ only applies when $Dependence_j$ equals zero. The same applies to the single term of $Dependence_j$.

The estimates of the other variables are similar to those in columns (1) to (4). The marginal effects of $cf_{i,j,t-1}$ are significantly positive and the marginal effects of $dbt_{i,j,t-1}$ are insignificant. These results indicate that firms' innovation activities are constrained by the availability of internal finance rather than external finance, and internal finance is the preferred source for supporting Chinese firms' innovation investments.

2.6.3. Effects of ownership and heterogeneity on firms' financing constraints

Given the capital market imperfections characterizing China, Chinese firms generally face a high premium for external finance. For instance, private firms, small and young firms face a high degree of financing constraints due to the 'lending bias' problem in China. To smooth R&D investment, these firms have to rely extensively on internal finance for R&D investments.

To test Hypothesis 3, we first compare SOEs with private firms because in China private firms are likely to face more financial constraints than SOEs. Table 2.3 presents the estimates of Eq. (2.7) for SOEs and private firms. We find that the marginal effects of the interaction term ($Competition_{j,t-1} * Dependence_j$) are significantly negative for both SOEs and private firms, while their magnitudes are greater for private firms than for SOEs, regardless of the measure of competition.[47] Specifically, in columns (2), (4), (6) and (8), the marginal effect of the interaction term for private firms is HHI -3.327%, EI -0.514%, LI (PCM) -3.017%

[47] In unreported results using the baseline Eq. (2.6) (without the interaction term), we also find that the marginal effect of $Competition_{j,t-1}$ on $np_{i,j,t}$ is more pronounced for private firms and financial constrained firms, i.e. private firms, small firms, young firms, firms without state shares, and firms in the central and western regions.

and FI -0.441%, while in columns (1), (3), (5) and (7) the corresponding figures for SOEs are HHI -2.157%, EI -0.495%, LI (PCM) -1.643% and FI -0.404%. We also conduct tests for the equality of the means of the interaction term between the two groups of firms, showing all the differences are significant at the 1% level. These results confirm Hypothesis 3 according to which in industries with higher EFD the negative effect of $Competition_{j,t-1}$ on $np_{i,j,t}$ is stronger for private firms than for SOEs. These results also suggest that more financial constraints faced by private firms further reinforce the negative impact of competition on innovation output in China.

[*Insert Table 2.3 here*]

The estimated marginal effects of $cf_{i,j,t-1}$ are significant and positive. This finding suggests that Chinese manufacturing firms face financing constraints. However, the magnitudes of our results suggest that the marginal effect of $cf_{i,j,t-1}$ for private firms is significantly greater than that for SOEs. Specifically, we find that the marginal effects of $cf_{i,j,t-1}$ for private firms range from 2.132% to 2.225% in columns (2), (4), (6) and (8), while those for SOEs range from 1.246% to 1.473% in columns (1), (3), (5) and (7). T-tests show the differences in $cf_{i,j,t-1}$ between SOEs and private firms are significant at the 1% level. These results suggest that the innovation activities of private firms are likely to face more financing constraints than those of SOEs. Due to the 'lending bias' and 'political pecking order' in China's financial market, private firms face more political obstacles to access external finance despite their higher efficiency and faster growth. In contrast, SOEs enjoy more financing advantages to alleviate financing constraints.

Next, we conduct additional tests for Hypothesis 3 by taking firm heterogeneity in the degree of financial constraints into account. Specifically, we re-estimate Eq. (2.7) splitting firms into sub-samples based on their size, age, state shares, and regions. The criteria for our classification are presented in Appendix D. Table 2.4 shows the corresponding estimation results. For brevity, we only report the results with industry competition computed using the HHI.[48]

[*Insert Table 2.4 here*]

Columns (1) to (4) in Table 2.4 present the estimation results based on firms' size and firms' age. As expected, the magnitudes of the marginal effects of the interaction term ($Competition_{j,t-1} * Dependence_j$) for small and young firms are significantly larger (-3.615% and -2.602% respectively) than those for large and mature firms (-2.492% and -2.416% respectively). Besides, the magnitude of the marginal effects of $cf_{i,j,t-1}$ is 1.404% for small firms and 2.255% for young firms, which are factually greater than the corresponding magnitudes for large (1.030%) and mature firms (1.623%). These results are in line with Hypothesis 3, suggesting that industry competition reduces innovation activities more for small and young firms in industries with higher EFD. Small or young firms are indeed more constrained by the availability of internal finance than large or mature firms.[49]

Columns (5) and (6) of Table 2.4 report the results based on firms' state shares. We observe that the magnitude of the marginal effect of the interaction term ($Competition_{j,t-1} * Dependence_j$) for firms without state shares (-2.634%) is significantly greater than that for firms with state shares (-1.601%). Moreover, the positive marginal effect of $cf_{i,j,t-1}$ for firms without state shares (1.846%) is significantly larger compared to their counterparts (0.896%),

[48] The estimation results are qualitatively the same when industry competition is quantified using the EI, the LI (PCM), and the FI separately.

[49] It is also worth noting that the magnitudes of the marginal effects of $np_{i,j,t-1}$ for small firms (52.184%) and young firms (49.224%) are greater than those for large firms (44.866%) and mature firms (46.319%), showing more persistence in small and young firms' innovation activities.

suggesting that the availability of internal finance represents a binding constraint for firms without state shares. These findings can be interpreted as firms without state shares are more likely to face financial constraints. They tend to reduce innovation output more when they face greater industry competition in higher EFD industries. By contrast, firms with more state shares can ease their financial constraints for their innovation activities by using their political connections through e.g. better borrowing conditions, waivers of import tariffs, tax reductions (Guariglia et al., 2011; Xu et al., 2013).

Finally, in columns (7) and (8) of Table 2.4, we further explore the difference between firms in the coastal regions and firms in the central and western regions. The magnitude of the marginal effect of the interaction term ($Competition_{j,t-1} * Dependence_j$) for firms in the central and western regions is significantly larger (-2.648%) than that for firms in the coastal regions (-2.229%). Besides, the marginal effect of $cf_{i,j,t-1}$ is positively higher for firms in the central and western regions (1.952%) than for their counterparts in the coastal regions (1.348%). These results suggest that the R&D activities of firms in the central and western regions face more financing constraints, which tightens the negative impact of competition on innovation. These findings may result from the imperfect system of financial development in the central and western provinces compared to the relatively well-developed system of financial development in coastal provinces. Therefore, firms in the central and western regions have difficulties obtaining external loans and face more financial constraints on innovation.

2.7. Endogeneity and robustness tests

While the above estimation results provide strong support for our hypotheses, there might be potential endogeneity issues due to reverse causality, potential measurement errors, and omitted variables. For example, industry competition could be endogenous if firms in an industry are inclined to engage in innovation, which might discourage other firms from entering the industry due to a high technology gap. In this case, more innovation will lead to less industry competition. Although in our baseline regressions we have lagged our independent variables, e.g., industry competition, to alleviate the simultaneity issue, in this section, we further proceed with several robustness tests to identify the causal relationship between industry competition and corporate innovation to mitigate endogeneity concerns.

2.7.1. Quasi-natural experiment

To provide clear identification of the causal effect of competition on innovation, we further use a quasi-natural experiment by exploiting plausible exogenous shocks to the intensity of industry competition in China. In the 1970s, China initiated market-oriented reforms and adopted a 'step-by-step' approach to opening industry to foreign investments. In 1995, the National Development and Reform Commission (NDRC) of China issued the first version of the 'Catalog of Industries to Guide Foreign Investment.' As a guide for foreign investment, the catalogue specifies sectors with more restrictions on foreign investment and those with fewer restrictions. There are four categories of sectors specified in the catalogue: 'encouraged, 'permitted,' 'restricted' and 'prohibited.' In 2002, the NDRC of China revised the catalogue in compliance with the regulations on China's WTO accession in December 2001.[50] Specifically, the number of 'encouraged' sectors increased from 186 to 262, and the number of 'restricted' ones decreased from 112 to 75, which provides exogenous changes to industry competition.[51]

This plausible exogenous policy (the revision of the catalogue in 2002) offers us an ideal quasi-natural experimental setting because of the shift in competitive intensity for several

[50] Fig. 2.1 shows that competitive intensity started to increase dramatically after 2002.

[51] The detailed 2002 revised catalogue can be found at http://www.fmprc.gov.cn/ce/cgsf/chn/kj/zyxx/t38777.htm.

industries. We hypothesize that it enhanced industry competition for firms in the sectors with a lifting of foreign investment restrictions, as opposed to those in the sectors with unchanged or increased restrictions on foreign investment. For example, before 2002 foreign investment in automobile manufacturing in China was restricted while after the catalogue revision, it became encouraged (although the Company Law still relatively limited the capital contribution of foreign partners). As a result, the number of firms in the automobile manufacturing industry increases by 170% from 190 to 516. We choose the automobile manufacturing industry (GB/T four-digit code: 3721) as the treatment group, and the metal ship manufacturing industry (GB/T four-digit code: 3751) as the control group since foreign investment in this industry remains unchanged. Another reason for choosing the metal ship manufacturing sector as the control group is that the two sectors share the same two-digit code (37 – manufacture of transport equipment), which can address potential confounding effects. We expect a reduction in new product output value in the treatment group (automobile manufacturing) and an increase in new product output value in the control group (metal ship manufacturing) following the catalogue revision in 2002.

Specifically, we use a difference-in-differences (DID) approach, which allows us to examine the extent to which there were changes in the innovation activities of the firms in the two groups. We construct a dummy variable $Treat$ that equals 1 for the treatment group and 0 for the control group, which captures the difference in $np_{i,j,t}$ before the revision. To control for common trends, we define $Post$ as a time dummy variable that equals one after 2002 and 0 otherwise, which captures aggregate factors that could cause changes in $np_{i,j,t}$ even in the absence of the revision in 2002.[52] To identify the causal effect of competition on innovation,

[52] To be consistent with our baseline regressions, we lag the time dummy variable ($Post$) to create the variable ($Post_{t-1}$).

we construct an interaction term ($Treat_j * Post_{t-1}$), which captures double differences in firms' innovation output between the treatment group and the control group and between the pre-treatment and post-treatment periods. We then revise our baseline Eq. (2.6) by including the dummy variable ($Treat$), the time dummy variable ($Post_{t-1}$) and the interaction term ($Treat * Post_{t-1}$), which produces the following equation:[53]

$$np_{i,j,t} = \beta_1 np_{i,j,t-1} + \beta_2 np^2_{i,j,t-1} + \beta_3 s_{i,j,t-1} + \beta_4 cf_{i,j,t-1} + \beta_5 dbt_{i,j,t-1} + \beta_6 Treat_j + \beta_7 Post_{t-1} + \beta_8 Treat_j * Post_{t-1} + V_i + V_o + V_r + e_{i,j,t} \quad (2.8)$$

Table 2.5 gives the results of the DID approach, which are estimates of Eq. (2.8) using the random-effect Tobit estimator. Our focus is on the interaction term ($Treat_j * Post_{t-1}$) because it captures the difference-in-differences effect on the changes over time (before and after the catalogue revision) in new product output value between firms in the treatment group and the control group. Our results in column (1) show that the marginal effect of the interaction term ($Treat_j * Post_{t-1}$) is significantly negative (-3.042%). This means that in response to the catalogue revision in 2002, firms in the automobile manufacturing sector reduced their innovation output by about 3.042% more than firms in the metal ship manufacturing sector. The unreported probability effects of the interaction term ($Treat_j * Post_{t-1}$) is also significantly negative (-6.636%), suggesting that the change in the probability of having innovation output from the pre- to post-revision periods was 6.636% lower for firms in the automobile manufacturing sector than those in the metal ship manufacturing sector. In line with Hypothesis 1, these results suggest that after the catalogue revision in 2002, automobile manufacturing firms (the treatment group) had a greater reduction in innovation output than

[53] In the regressions, we do not include the year dummy variable (V_t) or the industry dummy variable (V_j) because of collinearity.

metal ship manufacturing firms (the control group). This is because of the lifting of foreign investment restrictions in the automobile manufacturing sector, which led to greater industry competition in the treatment group.

[*Insert Table 2.5 here*]

The results in column (1) also reveal a significantly positive relationship between $np_{i,j,t}$ and $Treat_j$ and between $np_{i,j,t}$ and $Post_{t-1}$. These results suggest that before the revision, automobile manufacturing firms (the treatment group) were more likely to innovate than metal ship manufacturing firms (the control group). There is a significant improvement in firms' innovation output over time from the pre- to post-revision periods, even in the absence of the revision in 2002.

The key assumption for the consistency of the DID method is that of parallel trends. Economically, this assumption means that in the absence of the treatment, the average change in outcomes for both the treatment and control groups should be the same. To this end, in Fig. 2.4, we plot the average treatment and control response outcomes (innovation rates) from the pre- to post-revision periods. Specifically, first, it shows that the treatment group (automobile manufacturing, 3721) has higher average outcomes (innovation rates) than the control group (metal ship manufacturing, 3751). Second, both groups showed a similar trend in outcomes before the revision in 2002. However, after the onset of the catalogue revision in 2002, the innovation rate of the control group increased markedly, while that of the treatment group substantially decreased. Fig. 2.4 illustrates that our DID method satisfies the parallel trend assumption. These results provide more confidence that our DID estimates reflect a real causal effect of industry competition on corporate innovation.

[*Insert Fig. 2.4 here*]

To check internal validity, we also employ a falsification test in which we repeat the DID analysis on the pre-revision years. We change the onset year of treatment by defining $Post$ from 2002 to 2001 to 2000 in Eq. (2.8). In unreported results, we find the estimated marginal effects of the interaction term ($Treat_j * Post_{t-1}$) are no longer statistically significant. The falsification test confirms that our estimated DID effect is due to the treatment as opposed to some alternative force.

In column (2) of Table 2.5, we re-estimate Eq. (2.8) for the full sample. We manually split the sample into the treatment group (sectors with restrictions on foreign investment lifted after 2002) and the control group (sectors with unchanged or more restrictions after 2002). Specifically, after 2002 foreign investment restrictions were lifted for 66 GB/T four-digit sectors with 296,277 observations. We choose these 66 sectors as the treatment group and the other sectors as the control group. To further test Hypothesis 2, in column (3), we include the triple interaction term ($Treat_j * Post_{t-1} * Dependence_j$) in Eq. (2.8).

As expected, we find that the marginal effect of the interaction term ($Treat_j * Post_{t-1}$) remains significantly negative (-0.402%) in column (2). This result again shows that firms in the treatment group significantly reduced their innovation output compared to those in the control group in response to an increase in industry competition due to a lifting of restrictions on foreign investments after 2002. Furthermore, in column (3) the marginal effect of the triple interaction term ($Treat_j * Post_{t-1} * Dependence_j$) is statistically significant and negative (-1.945%), suggesting that the catalogue revision in 2002 reduced the innovation output of firms in industries with higher EFD more in the treatment group.[54] These results lend credence to Hypotheses 1 and 2.

In summary, our results indicate that following the exogenous policy shock in 2002, there was an increase in industry competition and an accompanying reduction in innovation, which was, however, restricted to the firms affected (the treatment group). Furthermore, the fall in innovation output affected firms in industries with higher EFD more than their counterparts in less EFD industries. The most important appeal of our DID approach is that it circumvents endogeneity issues by providing a plausible quasi-natural experimental setting. First, by providing a comparison with a control group, this approach rules out time-invariant unobserved factors in our innovation model, such as investment opportunities. Second, by providing a comparison between the pre-treatment and post-treatment periods, this approach rules out any common trends affecting both the treatment and control groups.

2.7.2. Instrumental variable (IV) method

In this section, we employ an instrumental variables (IV) approach with the Tobit estimator for baseline Eqs. (2.6) and (2.7). The instrumental variable for industry competition is the number of application procedures that a firm in China has to go through to enter a GB/T four-digit sector ($STEP_{j,t}$) each year (Cai & Liu, 2009).[55] This instrumental variable ($STEP_{j,t}$) measures the entry barriers in a GB/T four-digit sector imposed by the Chinese government each year. The more application procedures that a firm has to go through to enter a sector, the

[54] The probability effects of the interaction term ($Treat_j * Post_{t-1}$) in column (2) is -0.660% and the probability effects of the triple interaction term ($Treat_j * Post_{t-1} * Dependence_j$) in column (3) is -3.200%. Both effects are statistically significant at the 1% level.

[55] Special thanks go to Yupeng Shi at the Central University of Finance and Economics for providing information about the number of application procedures that a firm in China has to go through in order to enter a GB/T four-digit sector.

less competition that the sector faces. This instrumental variable ($STEP_{j,t}$) can be seen as an exogenous regulation of China's openness for different industries, which is negatively related to industry competitive intensity ($Competition_{j,t}$) while it is unlikely to be correlated with other variables influencing firms' innovation activities. Therefore, it satisfies the relevance and exclusion conditions. Specifically, we lag $STEP_{j,t}$ by one year ($STEP_{j,t-1}$) as an instrument for industry competitive intensity ($Competition_{j,t-1}$) in Eqs. (2.6) and (2.7).[56]

Panel A of Table 2.6 shows the IV Tobit estimation results. In columns (1) to (4), we instrument for industry competition ($Competition_{j,t-1}$) with $STEP_{j,t-1}$ in Eq. (2.6). We find that the results are similar to our baseline findings, although the magnitudes are somewhat larger. The marginal effects of the instrumented industry competitive intensity are negative and statistically significant at the 1% level. In columns (5) to (8), we re-estimate Eq. (2.7) by instrumenting for both the competition variable ($Competition_{j,t-1}$) and the interaction term ($Competition_{j,t-1} * Dependence_j$). In line with Hypothesis 2, we find a significant and negative marginal effect of the instrumented interaction term ($Competition_{j,t-1} * Dependence_j$) on firms' innovation activities. We also obtain qualitatively similar results by using the IV approach when we test Hypothesis 3, but for brevity, we do not report them. In short, using an instrumental variable ($STEP_{j,t-1}$) for industry competition ($Competition_{j,t-1}$) confirms our main conclusion that industry competition discourages innovation activities.

[*Insert Table 2.6 here*]

To evaluate the validity of the instrument, in unreported results we also find that there is a significantly negative relationship between $Competition_{j,t-1}$ and $STEP_{j,t-1}$ in our first-

[56] For the IV approach, we use GB/T four-digit sector codes as industry dummies in Eqs. (2.6) and (2.7) because the number of application procedures is based on GB/T four-digit codes.

stage regressions, suggesting the relevance condition is satisfied. The statistical first-stage F-values are significantly larger than the rule of thumb of 10, suggesting that the instrumental variable ($STEP_{j,t-1}$) is valid and does not suffer from a possible weak instrument bias (Stock and Yogo, 2005). To test the exclusion condition that the only role that the instrument $STEP_{j,t-1}$ plays in influencing innovation activities is through its effect on $Competition_{j,t-1}$, we also conduct a Wald test of exogeneity and an Anderson-Rubin test. Specifically, the Wald test measures whether the residuals from the reduced-form equation for the endogenous variables are correlated with error terms in the structural equation. Significant p-value statistics suggest that the regressors are not exogenous. The Anderson-Rubin (AR) test is a joint test of the structural parameter and the exogeneity of the instruments. The null hypothesis of the AR test is that all the regressors are exogenous, and the minimum canonical correlation is zero. Significant p-value statistics lower than 0.05 suggest that our model is identified and/or our instruments are valid. Additionally, we also conduct a Hausman test and a Smith-Blundell test to confirm the existence of (an) endogenous variable(s).

Furthermore, we assume that the other control variables are potentially endogenous. We re-estimate Eqs. (2.6) and (2.7) by instrumenting all the control variables. Specifically, we instrument the competition variable ($Competition_{j,t-1}$) with lagged values of the number of application procedures ($STEP_{j,t-1}$) and instrument the other control variables with their values lagged by two years. Panel B of Table 2.6 reports the corresponding estimation results, which remain consistent with our main regression results. All the instrument variables pass the validity tests too.

2.7.3. Alternative measurements of firms' innovation activities

A potential measurement error for firms' innovation activities and industry competition might yield biased and inconsistent estimates. In our main empirical analysis, we have used four proxies of industry competitive intensity to alleviate potential measurement errors of competition. In this section, we proceed with a robustness test using the number of patent applications and the ratio of R&D expenditure to total assets as alternative measures of firms' innovation output and innovation input. Specifically, we use the SIPO patent dataset processed by He et al. (2018) to merge with the NBS firm-level data through firms' legal person codes and then calculate the number of patent applications per firm. We then re-estimate Eqs. (2.6) and (2.7) by replacing $np_{i,j,t}$ with the natural logarithm of the number of patent applications plus one [$log\ (Patent_{i,j,t} + 1)$] and the ratio of R&D expenditure to total assets ($RD_{i,j,t}$) for firm i in industry j in year t.[57]

Table 2.7 presents the corresponding estimation results in which innovation is measured by the number of patent applications in Panel A and R&D expenditure in Panel B respectively. In columns (1) to (4), the marginal effects of industry competition on innovation are significantly negative at the 1% level, regardless of how we measure industry competition. Furthermore, in columns (5) to (8), five out of eight interaction terms ($Competition_{j,t-1} * Dependence_j$) are significantly negative. In short, these findings are in line with Hypotheses 1 and 2.

[*Insert Table 2.7 here*]

2.7.4. Augmented specifications with contemporaneous terms

An important caveat to our main results is that if omitted variables are related to the regressors, it can make correct statistical inferences hard to draw. To address this concern, following Brown et al. (2009), we add the contemporaneous terms of the right-hand side

[57] The estimation results are qualitatively the same when we estimate by Poisson or negative binomial models using patent counts as the dependent variable.

variables to Eqs. (2.6) and (2.7) to control for potential omitted variables that might drive innovation or the relationship between competition and innovation. Specifically, we include the contemporaneous competition variable ($Competition_{j,t}$) and its interaction term with the EFD variable ($Competition_{j,t} * Dependence_{j}$). As additional control variables for firm demand, we also add contemporaneous cash flow ($cf_{i,j,t}$), sales ($s_{i,j,t}$) and new long-term debt issues ($dbt_{i,j,t}$) in the regressions.

Table 2.8 shows the estimation results. We find that the results remain qualitatively unchanged: the sums of the marginal effects of industry competition and the interaction terms are significantly negative. Specifically, in columns (1) to (4), the lagged competition variable ($Competition_{j,t-1}$) has a more negative effect on $np_{i,j,t}$ (the marginal effects range from -0.195% to -6.868%) than the contemporaneous competition variable ($Competition_{j,t}$) (the marginal effects range from -0.079% to -4.036%). About the interaction term in columns (5) to (8), we find that the marginal effects of the interaction between the lagged competition variable and the EFD variable ($Competition_{j,t-1} * Dependence_{j}$) are significantly negative (HHI -2.125%, EI -0.468%, LI (PCM) -2.035% and FI -0.379%). In contrast, the marginal effects of the interaction between the contemporaneous competition variable and the EFD variable ($Competition_{j,t} * Dependency_{j}$) are insignificant. These results indicate that lagged industry competition has a more negative influence on firms' innovation activities than contemporaneous industry competition, even in industries with higher EFD. The finding can be explained by the fact that R&D projects are investments with a long-term return cycle, so industry competition has a lagged effect on innovation.

[*Insert Table 2.8 here*]

2.7.5. Market redefinition

In our main regression results, we define industries based on GB/T four-digit sector codes specified by the NBS in the national market, while it may be that not all enterprises compete nationwide. Young (2000) points out that China's regional protectionism and incremental reform process contribute to domestic market fragmentation. However, we believe that the problem could be alleviated in our main analysis for the following reasons. First, the sample data we choose is from 1998 to 2007. During this period, China was continually widening and deepening its market-oriented reforms, especially in manufacturing sectors (Holz, 2009), which may somewhat have relieved its regional protectionism. Second, the firms in our dataset are all 'above-scale' enterprises, which tend to operate and compete in the national market. Third, we include location dummies in all our regressions to control for uneven developments across regions.

However, to control for market fragmentation, following Cai and Liu (2009), we divide China into the eight market regions regulated by the State Council of China. We calculate competition intensity based on these eight economic regions. Using this new market definition, we re-estimate Eqs. (2.6) and (2.7) and find similar results, which are reported in Table 2.9.[58] Taking into account domestic market fragmentation, our main conclusions remain unchanged.

[*Insert Table 2.9 here*]

2.7.6. Other robustness tests

Besides the above tests, we also conduct other robustness analyses. First, we perform robustness tests using the random-effects Probit model in which the dependent variable is a

[58] Since we calculate the explanatory variable (competition intensity) based on the eight economic regions, we use 31 province-level administrative regions as the location dummy variables (V_p) instead.

binary variable taking one if a firm has a positive new product output value, and zero otherwise. The estimation results are shown in Table 2.10. Second, to take account of domestic market fragmentation, we recalculate industry competition based on the eight regional markets defined by China's central government. Third, we compute industry competitive intensity by using either the GB/T two-digit codes or the GB/T three-digit codes. Fourth, we cluster industries rather than firms. Fifth, we re-estimate our model by using a balanced sample to avoid our results being driven by the entry/exit of new/old firms. Sixth, we deal with the lack of data on the innovation variable for 2004 by using the average of the values for 2003 and 2005. We also ignore 2004 in our panel data and treat 2003 and 2005 as two consecutive years. Seventh, for external finance dependence, to control for the time effect on EFD and firm heterogeneity, we re-construct EFD by using the time series industry-level EFD ($Dependence_{j,t}$) and firm-level EFD ($Dependence_{i,j,t}$). The unreported results of all these robustness tests remain qualitatively the same.

[*Insert Table 2.10 here*]

2.8. Other extensions

2.8.1. Aggregate industry-level data on the period from 2001 to 2016

The NBS data used in our main regressions stops in 2007 because some key variables are not available after that. The 2017 FIND Report on City and Industrial Innovation in China provides the industry innovation index ($Innovation_{j,t}$) based on two-digit sector codes, which covers the years from 2001 to 2016 (Kou & Liu, 2017).[59] We merge the innovation index with the aggregate industry competition from the China Stock Market & Accounting Research

[59] The detailed information of industry innovation indexes are explained in the report, which can be retrieved from: http://imgcdn.yicai.com/uppics/files/2018/01/636507587751508252.pdf.

(CSMAR) Database. The first competition index is the industry Herfindahl index ($Herfindahl_{j,t}$), which is the sum of squared ratios of each listed firms' operating sales in one industry to all listed firms' operating sales in the industry. The second competition index is the industry Lerner index ($Lerner_{j,t}$), which is the weighted sum of each listed firms' Lerner index. To be specific, the firms' Lerner index is the ratio of each firms' operating profits to operation sales and the weight is the ratio of each firms' operating sales to all firms' operating sales in the industry. We use 1 minus the two indexes to build positive indicators of industry competition ($1 - Herfindahl_{j,t}$ and $1 - Lerner_{j,t}$).

The results are shown in Table 2.11. In columns (1) and (2) $Competition_{j,t-1}$ refers to the Herfindahl Index ($1 - Herfindahl_{j,t}$), whilst in columns (3) and (4) $Competition_{j,t-1}$ corresponds to the Lerner Index ($1 - Lerner_{j,t}$). We include industry and year fixed-effects to mitigate the time-invariant industry-specific effects and time-specific effects. In columns (1) and (3) we only include aggregate industry competition variable in the regressions, the coefficients of $Competition_{j,t-1}$ are significant and negative (-110.970 and -63.273), suggesting a negative relationship between competition and innovation based on industry-level. In columns (2) and (4), we add more industry-level control variables as in Eq. (2.6), which are total sales, total cash flows, and total new long-term debts.[60] All financial variables are scaled by industry-level total assets. The coefficients of $Competition_{j,t-1}$ have the expected negative sign (-118.062 and -70.016) and are statistically significant. In summary, based on an industry-level innovation index from the year 2001 to 2016, the estimation results confirm Hypothesis 1 again, according to which industry competition hurts innovation in China.

[60] In columns (3) and (4), we do not include lagged and squared terms of the industry innovation index because of the high collinearity (99.83%) between the lagged innovation variable and the contemporaneous innovation variable.

[*Insert Table 2.11 here*]

2.8.2. Exploring the inverted-U relationship between competition and innovation

Prior studies have explored the non-linear relationship between competition and innovation (Levin et al., 1985; Aghion et al., 2005) based on developed markets. We further address the concern of nonlinearity and test whether the inverted-U relationship can hold in China's market by including the squared term of competition variable ($Competition_{j,t-1} * Competition_{j,t-1}$) into baseline Eq. (2.6).

Columns (1) to (4) of Table 2.12 correspond to four different measures of competitive intensity. We find that only the estimation result of competition measured by the HHI in column (1) shows an explicit inverted-U relationship. Specifically, in column (1) the marginal effect of competition variable ($Competition_{j,t-1}$) is significantly positive and the squared competition variable ($Competition_{j,t-1} * Competition_{j,t-1}$) is significantly negative. However, based on the magnitudes of the competition variables (the HHI), we find that the turning point of the inverted-U relationship between competition and innovation (i.e., the quadratic graph goes from having an upward slope to a downward slope) is around 92.97%.[61] Given that the average value of the HHI is 98.48%, we find that approximately 96.97% of industries in our data sample have higher levels of competitive intensity than 92.97%. In other words, these results suggest that for the majority of industries in China, competitive intensity (the HHI) lies on the right- hand side of the quadratic graph, passing right through the turning

[61] Based on the magnitudes of the marginal effects of the competition variable ($Competition_{j,t-1}$) (370.53%) and the squared competition variable ($Competition_{j,t-1} * Competition_{j,t-1}$) (-199.28%), the turning point of competitive intensity (HHI) for the quadratic graph is 92.97%= 370.53% / (199.28% * 2).

point. Thus, the negative effect of competition on innovation is overpowering in China's industrial markets.

[*Insert Table 2.12 here*]

In columns (2) and (3) for the EI and the LI (PCM), both of the marginal effects of the squared competition variables are insignificant, which is not consistent with the inverted-U. In column (4), the estimation result based on the FI shows a U-shaped relationship between competition and innovation, suggested by the marginal effect of the competition variable ($Competition_{j,t-1}$) is significantly negative, and the marginal effect of the squared competition variable ($Competition_{j,t-1} * Competition_{j,t-1}$) is significantly positive. Similarly, we calculate that the turning point of the U-shaped relationship between competition and innovation (i.e., the quadratic graph goes from having a downward slope to an upward slope) is 10.67,[62] which is much higher than the average industry competitive intensity (6.87), measured by the FI. We find that all industry competition in our sample lies on the left-hand side of the quadratic graph, passing left through the turning point. The findings suggest that the negative effect of competition on innovation plays a dominating role in China's industrial market. To sum up, we confirm the vast majority of sectors in China are 'laggard-and-laggard' which is indicated by the data.

2.8.3. Exploring the mechanism through intellectual property rights (IPRs) protection

We attribute the negative effect of competition on innovation to intense competition in the Chinese manufacturing industry with difficulties obtaining sufficient finance. However, it could be possible that without the protection of intellectual property rights, innovation is likely to be imitated and expropriated by competitors. A common strategy in China is that once there

[62] The turning point of competitive intensity (FI) for the quadratic graph is 10.67= 0.704% / (0.033% * 2).

is a potentially successful innovation, their competitors will imitate these products or business models to escape competition and gain more market shares (Allen et al., 2019). With a higher likelihood of imitation, more competition is associated with a higher risk of R&D failure, which will discourage more corporate innovation. For example, Fang et al. (2017) document that IPRs protection plays an important role in corporate innovation in China.

To test whether IPRs protection could influence the impact of competition on innovation, we include an interaction term between the competition variable and IPRs protection scores and re-estimate Eq (2.6).[63] A higher score of IPRs protection represents a better quality of local IPRs protection. The estimation results in Table 2.13 show the significantly positive marginal effects of the interaction terms between competition and IPRs protection scores. The finding suggests that weak IPRs protection enhances the negative impact of industry competition on innovation. These results suggest that IPRs protection acts as an alternative mechanism through which industry competition affects firms' innovation activities.

[*Insert Table 2.13 here*]

2.8.4. Exploring the mechanism between competition and cash flow

In this subsection, we provide an additional test by adding an interaction term between the competition variable and the cash flow variable to check whether increased competition leads to more financial constraints on firms' innovation activities. According to the 'Schumpeterian theory' (Schumpeter, 1943), increased competition should reduce firms' profits, which adversely affects the internal and external finance premiums for innovation investment. In this subsection, we provide an additional test by adding an interaction term

[63] Our IPRs data is a province-level index of IPRs protection from 1998 to 2007, which is developed by the National Economic Research Institute (NERI) of China (Fan et al., 2016).

between the competition variable and the cash flow variable to check whether increased competition leads to more financial constraints on firms' innovation activities. Given that the sensitivity of R&D investment to cash flow can reflect the level of financial constraints, we expect increased industry competition to lead to an increase in the R&D-cash flow relationship.

Table 2.14 reports the estimation results. Specifically, we find the marginal effects of the interaction term ($Competition_{j,t-1} * cf_{i,j,t-1}$) are significantly positive (49.317%, 1.299%, 15.962% and 1.436%). This finding suggests that as competition increases, firms' innovation activities face more financial constraints. Therefore, firms have to rely more on internal finance for innovation investment. When we introduce the interaction term ($Competition_{j,t-1} * cf_{i,j,t-1}$), the marginal effects of cash flow ($cf_{i,j,t-1}$) are not particularly interesting since they only apply at the specific point when $Competition_{j,t-1}$ equals zero. Besides, the marginal effects of the interaction term ($Competition_{j,t-1} * Dependence_j$) are significantly negative, which leaves all of our main conclusions unchanged. The results show that increased industry competition leads to a tightening of the R&D-cash flow relationship. This finding suggests that as competition increases, firms' innovation activities face more financial constraints. Therefore, firms have to rely more on internal finance for innovation investments.

[*Insert Table 2.14 here*]

2.9. Conclusions

Focusing on a relatively large firm-level database over the period 1998 to 2007, we have shown that there is a negative relationship between firms' innovation activities and industry competition in China, suggesting that China's manufacturing sector is dominated by laggard firms with high competition. We have found that the negative relation is stronger in industries that are more dependent on external finance. Further evidence shows that financing constraints tighten the negative effect of competition on innovation and R&D-cash flow sensitivity.

This research contributes to the understanding of China's unconventional growth path and innovation hurdle (negative impact of industry competition). We believe this is an important contribution considering the important role of innovation in shaping growth strategies in emerging market economies. Today, with the challenge of rising labour costs and the squeeze from newly emerging low-cost producers, the leading advantages of China's manufacturing are under threat. Industrial upgrading (moving from 'laggard-and-laggard' to 'neck-and-neck') and innovation will be critical if China tends to maintain its position as a global manufacturing powerhouse. To this end, the Chinese government needs to deepen structural reforms to rein in surplus production capacity and over-competition. Strategically, the Chinese government needs to upgrade low-end manufacturing to the high end of global value chains and high-tech industries to promote high-quality development. Related policies, e.g., strengthening intellectual property protection and R&D tax relief could help to encourage more innovation activities and upgrade industry structure.

Regarding external finance dependence (EFD) and financing constraints on corporate innovation, China also needs to make more efforts to deepen its financial system reform. Despite several positive steps, e.g., the financial reforms outlined by the Communist Party Central Committee's Third Plenum in 2013, the financial system in China is relatively weak. There still exists a 'lending bias problem' and 'institutional discrimination' in allocating financial capital to firms. More policies are needed to enhance the market's role in allocating resources and breaking financing obstacles to support innovation investment, especially for firms facing financial constraints. Meanwhile, policies could be implemented to regulate industries' leverage ratios and prevent a destabilizing build-up of debt. Avoiding overwhelming dependence on external finance and lowering firms' financial constraints would therefore benefit corporate innovation.

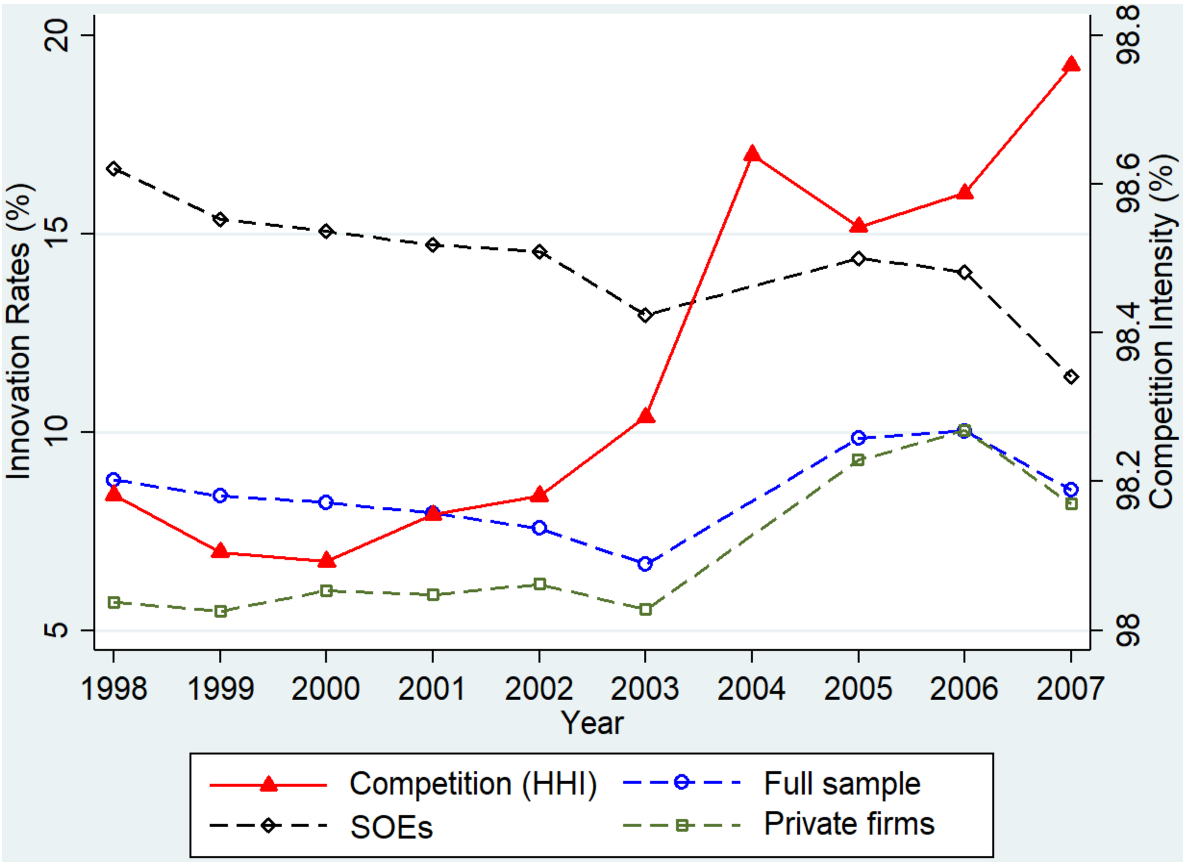
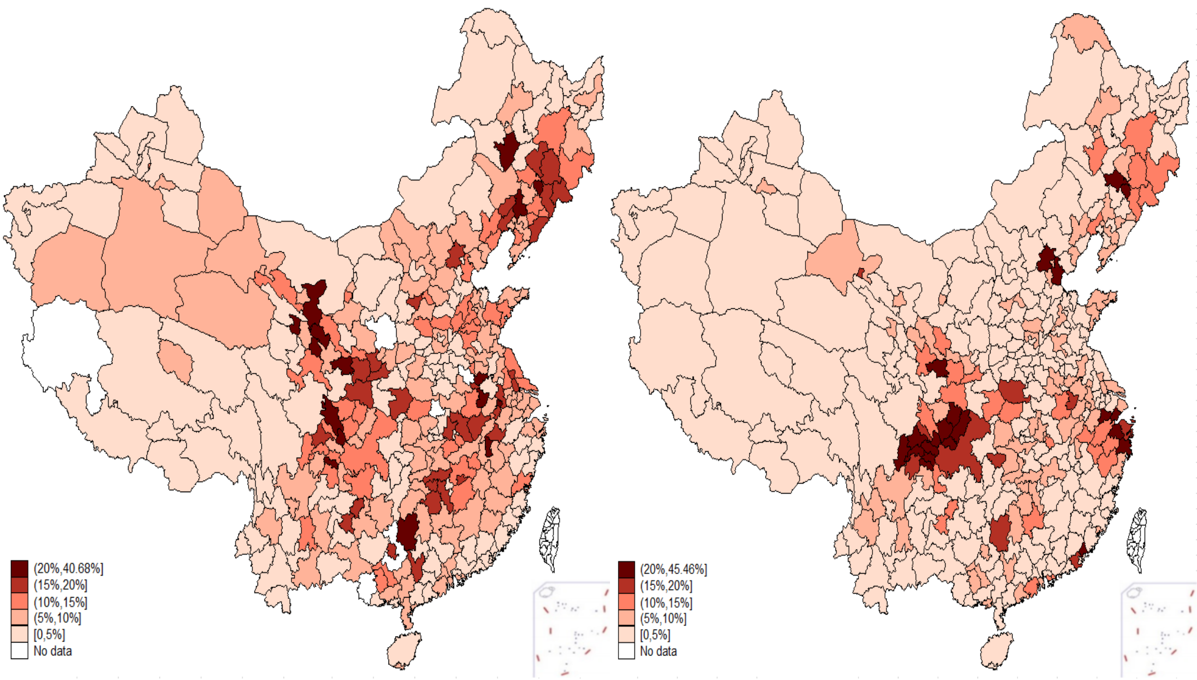


Figure 2.1. Innovation rates and industry competition in China from 1998 to 2007



1998 2007

Figure 2.2. Average innovation rates in prefecture-level administrative divisions in China

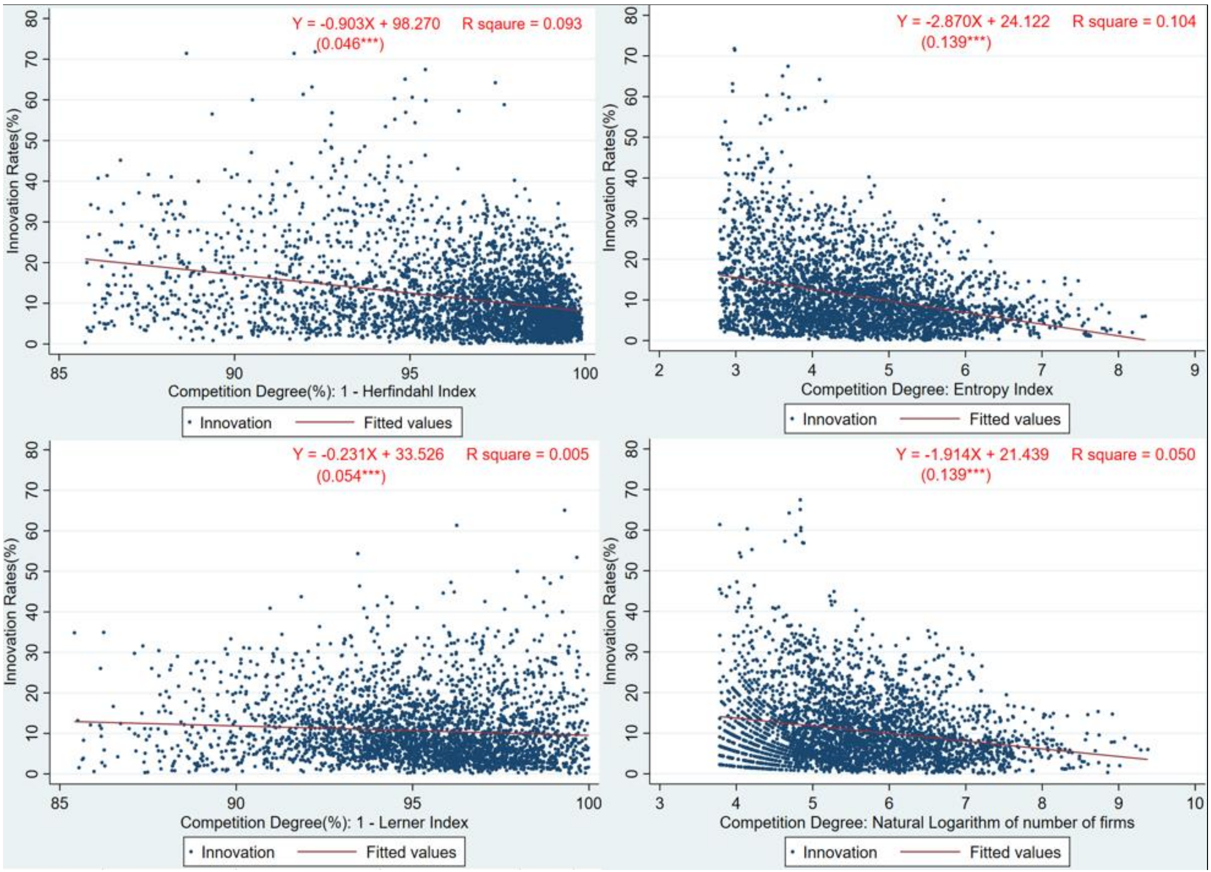


Figure 2.3. Average innovation rates vs. industry competition for GB/T four-digit sector codes in China from 1998 to 2007

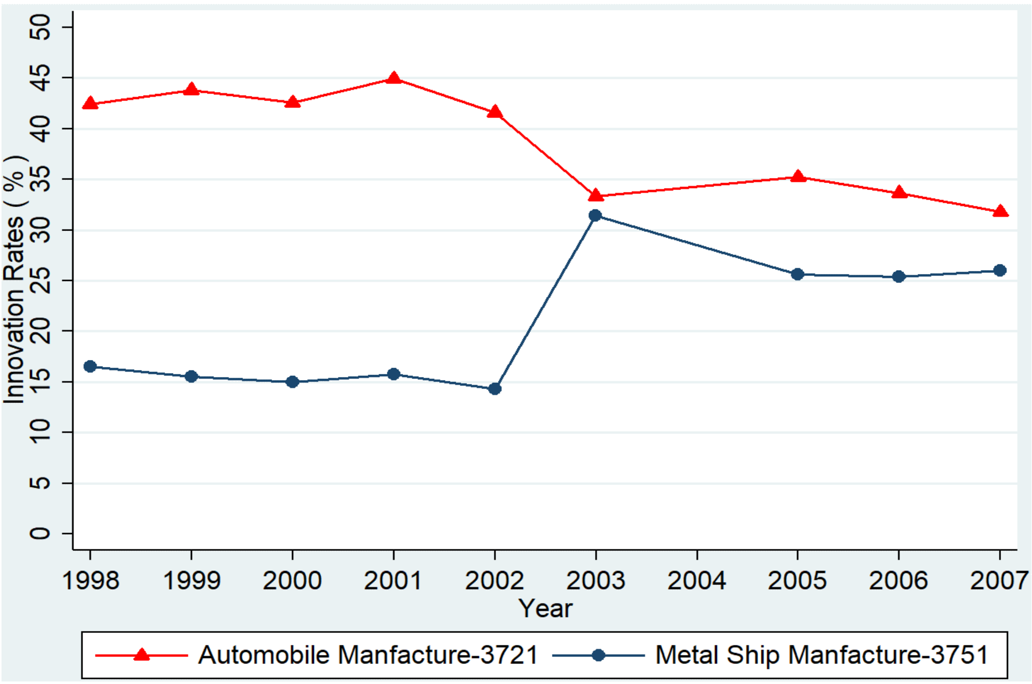


Figure 2.4. Trend line comparison from 1998 to 2007. Note: The figure illustrates the time trends of the innovation rates of the treatment group (i.e., automobile manufacturing firms with GB/T four-digit code 3721) and the control group (i.e., metal ship manufacturing firms with GB/T four-digit code 3751)

Chapter 2

China’ innovation hurdle: competition and finance

Table 2.1
Summary statistics - Sample means and medians (in parentheses)

	Full sample	New Products = 0	New Products > 0	SOEs	Private firms	*Diff1*	*Diff2*
Main regression variables							
New product output value / total assets	2.626	0.000	30.232	2.678	2.890	0.00	0.00
	(0.000)	(0.000)	(20.125)	(0.000)	(0.000)		
Log (number of patent applications plus 1)	0.031	0.023	0.110	0.037	0.026	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
R&D expenditure / total assets	0.094	0.065	0.396	0.110	0.091	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Competition [HHI]	98.476	98.517	98.047	98.004	98.631	0.00	0.00
	(99.162)	(99.177)	(98.858)	(98.725)	(99.242)		
Competition [EI]	5.777	5.807	5.463	5.397	5.920	0.00	0.00
	(5.728)	(5.771)	(5.408)	(5.384)	(5.934)		
Competition [LI (PCM)]	94.927	94.954	94.637	96.404	94.507	0.00	0.00
	(94.901)	(94.902)	(94.555)	(96.677)	(94.528)		
Competition [FI]	6.866	6.891	6.603	6.640	7.007	0.00	0.00
	(6.835)	(6.862)	(6.568)	(6.707)	(7.011)		
Industry external finance dependence	58.570	58.708	57.127	65.237	58.459	0.00	0.00
	(58.139)	(58.139)	(57.050)	(67.543)	(58.139)		
Sales / total assets	187.942	194.123	123.060	87.454	223.811	0.00	0.00
	(127.183)	(132.408)	(88.818)	(58.229)	(157.331)		
Cash flow / total assets	9.624	9.788	7.906	4.064	10.793	0.00	0.00
	(5.965)	(6.040)	(5.294)	(2.888)	(6.460)		
New long-term debt issue / total assets	-0.047	-0.048	-0.039	-0.251	0.058	0.72	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Variables related to financial constraints							
Total assets	108.128	83.682	365.125	336.687	41.151	0.00	0.00
	(19.754)	(18.224)	(63.150)	(56.868)	(13.506)		
Age	12.209	11.704	17.519	26.747	9.779	0.00	0.00
	(8.000)	(8.000)	(10.000)	(26.000)	(7.000)		
Percentage of state shares	9.723	9.082	16.457	93.117	0.323	0.00	0.00
	(0.000)	(0.000)	(0.000)	(100.000)	(0.000)		
Observations	693,748	633,493	60,255	66,978	260,919		

Notes: Total assets are expressed in millions of yuan. All other variables except Log (number of patent applications plus 1), Competition [EI], Competition [FI], and age are shown in percentage terms. *Diff1* and *Diff2* are the p-values associated with the mean-equality test between the group with a new product output value > 0 and the group with a new product output value= 0 (*Diff1*) and between the SOE group and the private firm group (*Diff2*). Complete definitions of all variables are shown in Appendix D.

Table 2.2
Modified baseline Euler equations (2.6) and (2.7) for the full sample

	Eq. (2.6)				Eq. (2.7)			
	HHI (1)	EI (2)	LI (PCM) (3)	FI (4)	HHI (5)	EI (6)	LI (PCM) (7)	FI (8)
$Competition_{j,t-1}$	-9.157***	-0.322***	-4.952***	-0.266***	-9.158***	-0.051	-1.655*	-0.036
	[0.869]	[0.019]	[0.816]	[0.019]	[0.919]	[0.042]	[0.937]	[0.040]
$Competition_{j,t-1} * Dependence_j$					-2.487***	-0.474***	-2.241***	-0.437***
					[0.437]	[0.066]	[0.453]	[0.060]
$Dependence_j$					0.465	0.711*	0.604	1.062***
					[0.433]	[0.376]	[0.433]	[0.406]
$np_{i,j,t-1}$	45.040***	45.012***	45.335***	45.131***	45.159***	45.274***	45.436***	45.260***
	[0.268]	[0.268]	[0.268]	[0.268]	[0.270]	[0.271]	[0.271]	[0.270]
$np^2_{i,j,t-1}$	-31.092***	-31.070***	-31.217***	-31.107***	-31.221***	-31.290***	-31.353***	-31.236***
	[0.271]	[0.271]	[0.272]	[0.271]	[0.274]	[0.276]	[0.275]	[0.275]
$s_{i,j,t-1}$	-0.789***	-0.787***	-0.796***	-0.787***	-0.787***	-0.789***	-0.794***	-0.785***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
$cf_{i,j,t-1}$	1.934***	1.929***	1.869***	1.927***	1.814***	1.766***	1.791***	1.818***
	[0.177]	[0.177]	[0.178]	[0.177]	[0.179]	[0.179]	[0.180]	[0.179]
$dbt_{i,j,t-1}$	-0.143	-0.164	-0.165	-0.122	-0.211	-0.192	-0.221	-0.174
	[0.229]	[0.229]	[0.231]	[0.230]	[0.231]	[0.233]	[0.233]	[0.232]
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.273	0.273	0.270	0.272	0.273	0.270	0.270	0.271
Firms	289,738	289,472	288,525	289,486	284,671	283,548	283,627	284,242
Observations	693,748	693,152	688,599	693,044	679,512	673,098	675,328	677,991
Left − censored	633,493	633,053	628,027	632,955	620,100	614,319	615,781	618,997
Uncensored	60,255	60,099	60,572	60,089	59,412	58,779	59,547	58,994

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3
Modified baseline Euler equation (2.7): between SOEs and private firms

	HHI		EI		LI (PCM)		FI	
	SOEs	Private	SOEs	Private	SOEs	Private	SOEs	Private
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,t-1}$	-6.115***	-8.498***	-0.033	0.009	-3.237**	-2.750	-0.006	0.001
	[1.420]	[1.833]	[0.075]	[0.082]	[1.390]	[1.938]	[0.069]	[0.078]
$Competition_{j,t-1} * Dependence_j$	-2.157***	-3.327***	-0.495***	-0.514***	-1.643**	-3.017***	-0.404***	-0.441***
	[0.709]	[0.904]	[0.113]	[0.128]	[0.746]	[0.934]	[0.102]	[0.120]
$Dependence_j$	-0.091	0.372	0.107	0.201	-0.012	0.414	0.253	0.333
	[0.698]	[0.897]	[0.601]	[0.751]	[0.717]	[0.890]	[0.650]	[0.822]
$np_{i,j,t-1}$	35.563***	52.639***	35.645***	52.653***	36.453***	52.576***	35.482***	52.562***
	[0.470]	[0.490]	[1.380]	[0.485]	[0.481]	[0.489]	[0.471]	[0.488]
$np^2_{i,j,t-1}$	-22.415***	-35.832***	-22.594***	-35.778***	-23.065***	-35.731***	-22.520***	-35.726***
	[0.526]	[0.495]	[0.979]	[0.494]	[0.537]	[0.495]	[0.529]	[0.494]
$s_{i,j,t-1}$	-0.806***	-0.909***	-0.780***	-0.909***	-0.842***	-0.906***	-0.796***	-0.897***
	[0.054]	[0.026]	[0.061]	[0.026]	[0.056]	[0.026]	[0.054]	[0.026]
$cf_{i,j,t-1}$	1.381***	2.225***	1.362***	2.152***	1.246***	2.132***	1.473***	2.149***
	[0.459]	[0.322]	[0.466]	[0.323]	[0.477]	[0.323]	[0.461]	[0.322]
$dbt_{i,j,t-1}$	-0.256	-0.056	-0.240	0.020	-0.259	0.009	-0.291	0.040
	[0.355]	[0.445]	[0.359]	[0.446]	[0.368]	[0.446]	[0.359]	[0.445]
Diff1 (p − value)	(0.000)***		(0.000)***		(0.000)***		(0.000)***	
Diff2 (p − value)	(0.000)***		(0.000)***		(0.000)***		(0.000)***	
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.333	0.155	0.332	0.153	0.337	0.157	0.340	0.155
Firms	27,378	139,682	26,895	139,423	26,706	139,466	27,190	139,621
Observations	64,027	256,733	62,595	255,500	61,227	256,164	63,675	256,525
Left − censored	54,254	235,728	53,044	234,566	51,578	235,039	54,132	235,555
Uncensored	9,773	21,005	9,551	20,934	9,649	21,125	9,543	20,970

Notes: This table reports marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Diff1 (p-value) is the p-value for the difference in the marginal effects of the interaction term between the group of SOEs and the group of private firms. Diff2 (p-value) is the p-value for the difference in the marginal effects of lagged cash flow between the group of SOEs and the group of private firms. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4
Modified baseline Euler equation (2.7): differentiating firms based on size, age, state shares and region

	Size		Age		State shares		Region	
	Small	Large	Young	Mature	No	With	Coastal	Central and Western
	(1)	(2)	(3)	(4)	(5)	(6)	(11)	(12)
$Competition_{j,t-1}$	-12.339***	-9.375***	-11.749***	-6.882***	-9.604***	-5.697***	-8.182***	-10.566***
	[1.590]	[1.191]	[1.339]	[1.240]	[1.099]	[1.397]	[1.157]	[1.506]
$Competition_{j,t-1} * Dependence_j$	-3.615***	-2.492***	-2.602***	-2.416***	-2.634***	-1.601**	-2.229***	-2.648***
	[0.813]	[0.558]	[0.661]	[0.595]	[0.530]	[0.664]	[0.537]	[0.736]
$Dependence_j$	1.091	0.633	0.307	0.671	0.495	-0.292	0.996*	-0.277
	[0.805]	[0.554]	[0.655]	[0.591]	[0.526]	[0.654]	[0.533]	[0.729]
$np_{i,j,t-1}$	52.184***	44.866***	49.224***	46.319***	49.006***	37.432***	43.766***	44.878***
	[0.529]	[0.329]	[0.405]	[0.349]	[0.315]	[0.451]	[0.358]	[0.446]
$np^2_{i,j,t-1}$	-37.722***	-29.587***	-34.336***	-31.610***	-33.934***	-23.706***	-29.427***	-33.470***
	[0.539]	[0.335]	[0.414]	[0.362]	[0.320]	[0.490]	[0.345]	[0.490]
$s_{i,j,t-1}$	-0.600***	-0.644***	-0.817***	-0.784***	-0.829***	-0.810***	-1.021***	-0.493***
	[0.023]	[0.025]	[0.023]	[0.023]	[0.018]	[0.049]	[0.023]	[0.022]
$cf_{i,j,t-1}$	1.404***	1.030***	2.255***	1.623***	1.846***	0.896**	1.348***	1.952***
	[0.279]	[0.257]	[0.255]	[0.252]	[0.201]	[0.425]	[0.246]	[0.256]
$dbt_{i,j,t-1}$	-1.328***	0.055	0.096	-0.392	-0.337	0.13	0.059	-0.251
	[0.446]	[0.287]	[0.351]	[0.312]	[0.280]	[0.350]	[0.317]	[0.322]
Diff1 (p − value)	(0.000)***		(0.000)***		(0.000)***		(0.000)***	
Diff2 (p − value)	(0.000)***		(0.000)***		(0.000)***		(0.000)***	
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.172	0.287	0.199	0.269	0.215	0.344	0.307	0.228
Firms	178,965	142,940	197,952	137,859	262,643	35,041	206,406	78,537
Observations	343,480	336,032	370,119	309,385	597,325	82,180	499,665	179,847
Left − censored	327,381	292,719	343,281	276,811	551,228	68,867	459,963	160,137
Uncensored	16,099	43,319	26,838	32,574	46,097	13,313	39,702	19,710

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Diff1 (p-value) is the p-value for the difference in the marginal effects of the interaction term between two groups. Diff2 (p-value) is the p-value for the difference in the marginal effects of lagged cash flow between the two groups. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5
Modified baseline Euler Equation (2.8) using the difference-in-differences (DID) approach

	(1)	(2)	(3)
$Treat_j$	3.865***	0.707***	0.499***
	[0.888]	[0.070]	[0.070]
$Post_{t-1}$	2.525***	0.997***	1.024***
	[0.881]	[0.039]	[0.039]
$Treat_j * Post_{t-1}$	-3.042***	-0.402***	0.558**
	[1.066]	[0.087]	[0.272]
$Treat_j * Post_{t-1} * Dependence_j$			-1.945***
			[0.491]
$Dependence_j$			-3.680***
			[0.152]
$np_{i,j,t-1}$	67.113***	47.741***	47.579***
	[2.863]	[0.276]	[0.277]
$np^2_{i,j,t-1}$	-37.955***	-33.149***	-33.065***
	[2.885]	[0.278]	[0.280]
$s_{i,j,t-1}$	-1.942***	-0.853***	-0.857***
	[0.348]	[0.016]	[0.016]
$cf_{i,j,t-1}$	2.335	1.237***	1.151***
	[3.924]	[0.177]	[0.178]
$dbt_{i,j,t-1}$	1.517	-0.137	-0.218
	[3.699]	[0.226]	[0.229]
Prob > chi2	0.000	0.000	0.000
Rho	0.128	0.278	0.275
Firms	1,286	291,241	286,547
Observations	2,785	700,491	687,609
Left − censored	1,890	639,291	627,216
Uncensored	895	61,200	60,393

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Ownership and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6
Modified baseline Euler equations (2.6) and (2.7) using the IV Tobit for the full sample ($Competition_{j,t-1}$ is instrumented with $STEP_{j,t-1}$)

	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: only $Competition_{j,t-1}$ is instrumented							
$Competition_{j,t-1}$	-487.168***	-5.572***	-89.325***	-5.108***	-173.059***	-2.534***	-1.931	-0.655
	[69.790]	[0.755]	[11.192]	[0.622]	[29.082]	[0.667]	[10.431]	[0.446]
$Competition_{j,t-1} * Dependence_j$					-35.001***	-4.861***	-67.724***	-6.668***
					[4.459]	[1.057]	[7.599]	[0.980]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\text{Prob} > \text{chi2}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wald test of exogeneity (p − value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anderson − Rubin (p − value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	271,262	271,094	271,901	271,066	268,152	267,001	268,528	267,738
Observations	647,893	647,446	650,171	647,205	638,614	631,836	640,124	636,842
Left − censored	588,593	588,295	590,441	588,067	580,098	573,919	581,364	578,709
Uncensored	59,300	59,151	59,730	59,138	58,516	57,917	58,760	58,133
	Panel B: all other independent variables are instrumented							
$Competition_{j,t-1}$	-128.784	-4.550***	-75.565***	-3.830***	-196.789***	-1.506**	26.219	-0.463
	[82.091]	[0.589]	[14.235]	[0.683]	[21.906]	[0.698]	[16.827]	[0.528]
$Competition_{j,t-1} * Dependence_j$					-26.879***	-4.126***	-82.798***	-4.543***
					[8.594]	[0.966]	[19.927]	[0.832]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\text{Prob} > \text{chi2}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wald test of exogeneity (p − value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anderson − Rubin (p − value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	200,917	200,795	201,614	200,888	198,638	198,280	199,149	198,439
Observations	411,751	411,324	413,730	411,545	406,076	403,051	407,412	405,115
Left − censored	371,019	370,723	372,642	370,889	365,871	363,246	366,988	365,142
Uncensored	40,732	40,601	41,088	40,656	40,205	39,805	40,424	39,973

Notes: This table reports the marginal effects as percentages using the IV Tobit method. The marginal effects are shown as percentages. When we use the IV Tobit, the dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. In panel A, we instrument the competition variable with the number of application procedures a firm has to go through to enter a GB/T four-digit industry. In panel B, we further instrument all the other control variables with their lagged values. Wald test of exogeneity is distributed as chi-square under the null hypothesis of exogeneity. Anderson-Rubin is under the null hypothesis that the minimum canonical correlation is zero. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7
Modified baseline Euler Equations (2.6) and (2.7) for the full sample with alternative measures of firms' innovation activities

	Panel A: an alternative measurement of innovation activities (i.e. patent number, labelled as Log (Patent + 1)							
	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,t-1}$	-70.340***	-2.627***	-30.546***	-2.193***	-70.102***	-2.221***	-38.177***	-2.027***
	[3.571]	[0.084]	[3.459]	[0.084]	[3.746]	[0.159]	[3.867]	[0.142]
$Competition_{j,t-1} * Dependence_j$					-2.136	-0.753***	0.988	-0.362*
					[1.510]	[0.254]	[1.588]	[0.215]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.323	0.322	0.332	0.324	0.320	0.317	0.328	0.321
Firms	300,187	300,080	299,306	300,139	295,108	294,161	294,168	295,008
Observations	909,535	913,754	908,595	913,887	891,284	888,346	890,354	893,379
Left − censored	870,051	874,331	868,625	874,285	852,446	849,526	851,113	854,355
Uncensored	39,484	39,423	39,970	39,602	38,838	38,820	39,241	39,024

	Panel B: an alternative measurement of innovation activities (i.e. R&D expenditures/total assets, labelled as RD)							
	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,t-1}$	-0.474***	-0.015***	-0.286***	-0.011***	-0.518***	-0.012***	-0.246***	-0.008***
	[0.030]	[0.001]	[0.030]	[0.001]	[0.031]	[0.001]	[0.033]	[0.001]
$Competition_{j,t-1} * Dependence_j$					-0.032**	-0.007***	-0.019	-0.006***
					[0.013]	[0.002]	[0.014]	[0.002]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.285	0.285	0.284	0.285	0.286	0.288	0.285	0.287
Firms	253,768	253,503	252,432	253,695	248,514	247,490	248,089	248,984
Observations	518,529	518,028	515,475	518,650	506,500	502,507	504,222	508,149
Left − censored	453,987	453,675	450,543	454,134	443,955	440,359	441,340	445,350
Uncensored	64,542	64,353	64,932	64,516	62,545	62,148	62,882	62,799

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. In Panel A, the dependent variable $Log\ (Patent + 1)_{i,j,t}$ is the natural logarithm of the number of patent applications plus one. In Panel B, the dependent variable $RD_{i,j,t}$ is the ratio of R&D expenditure to total assets. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.8
Modified augmented Euler equations (2.6) and (2.7): accounting for the contemporaneous terms

	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,t}$	-4.036***	-0.113**	-2.709**	-0.079	-2.668	-0.197*	-1.702	-0.001
	[1.515]	[0.046]	[1.254]	[0.048]	[4.462]	[0.104]	[3.563]	[0.102]
$Competition_{j,t-1}$	-6.868***	-0.221***	-2.762**	-0.195***	-6.400***	0.033	0.169	0.001
	[1.472]	[0.046]	[1.197]	[0.048]	[1.518]	[0.060]	[1.310]	[0.059]
$\boldsymbol{Sum\ (Competition)}$	-10.903***	-0.334***	-5.471***	-0.274***	-9.068**	-0.164*	-1.532	0.000
	[0.985]	[0.020]	[0.941]	[0.020]	[4.304]	[0.088]	[3.479]	[0.086]
$Competition_{j,t} * Dependence_j$					-3.841	0.171	-1.499	-0.150
					[7.140]	[0.163]	[5.429]	[0.159]
$Competition_{j,t-1} * Dependence_j$					-2.125***	-0.468***	-2.035***	-0.379***
					[0.454]	[0.077]	[0.467]	[0.070]
$\boldsymbol{Sum\ (Competition * Dependence_j)}$					-5.966	-0.297**	-3.534	-0.530***
					[7.116]	[0.144]	[5.430]	[0.142]
$Dependence_j$					3.894	-0.192	1.978	1.682*
					[6.987]	[0.822]	[5.122]	[0.955]
$np_{i,j,t-1}$	45.270***	45.073***	45.517***	45.173***	45.388***	45.324***	45.608***	45.268***
	[0.274]	[0.273]	[0.274]	[0.273]	[0.276]	[0.276]	[0.277]	[0.276]
$np^2_{i,j,t-1}$	-31.250***	-31.097***	-31.340***	-31.095***	-31.370***	-31.322***	-31.473***	-31.190***
	[0.277]	[0.277]	[0.277]	[0.276]	[0.280]	[0.281]	[0.280]	[0.280]
$s_{i,j,t}$	-0.313***	-0.312***	-0.325***	-0.315***	-0.309***	-0.308***	-0.321***	-0.309***
	[0.021]	[0.021]	[0.022]	[0.021]	[0.022]	[0.022]	[0.022]	[0.022]
$s_{i,j,t-1}$	-0.587***	-0.581***	-0.591***	-0.579***	-0.589***	-0.584***	-0.591***	-0.577***
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
$cf_{i,j,t}$	1.653***	1.790***	1.666***	1.754***	1.602***	1.710***	1.627***	1.752***
	[0.210]	[0.210]	[0.212]	[0.210]	[0.212]	[0.212]	[0.213]	[0.212]
$cf_{i,j,t-1}$	1.185***	1.100***	1.132***	1.109***	1.092***	0.976***	1.088***	1.092***
	[0.222]	[0.222]	[0.223]	[0.222]	[0.224]	[0.225]	[0.225]	[0.225]
$dbt_{i,j,t}$	0.404	0.359	0.377	0.343	0.361	0.352	0.330	0.323
	[0.252]	[0.252]	[0.254]	[0.252]	[0.254]	[0.255]	[0.256]	[0.255]
$dbt_{i,j,t-1}$	-0.074	-0.108	-0.127	-0.086	-0.132	-0.131	-0.170	-0.072
	[0.243]	[0.243]	[0.245]	[0.243]	[0.245]	[0.246]	[0.247]	[0.247]
$\text{Prob} > \text{chi2}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.271	0.273	0.268	0.272	0.271	0.271	0.268	0.272
Firms	279,517	278,836	277,588	279,086	274,569	273,105	272,949	273,238
Observations	663,751	660,177	661,608	660,718	650,083	640,915	649,045	640,492
$\text{Left} - \text{censored}$	605,395	602,152	602,729	602,591	592,517	584,238	591,164	583,844
Uncensored	58,356	58,025	58,879	58,127	57,566	56,677	57,881	56,648

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. **Sum (Competition)** is s the sum of the marginal effects of the contemporaneous term and the lagged term of competition variables. **Sum (Competition* Dependence)** is the sum of the marginal effects of the contemporaneous interaction term and the lagged interaction term between competition and industry external finance dependence. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.9
Modified baseline Euler equations (2.6) and (2.7): accounting for domestic market fragmentation

	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,r,t-1}$	-3.612***	-0.335***	-1.308**	-0.285***	-2.924***	-0.152***	-0.395	-0.144***
	[0.219]	[0.017]	[0.543]	[0.017]	[0.288]	[0.034]	[0.611]	[0.031]
$Competition_{j,r,t-1} * Dependence_{j,r}$					-1.402***	-0.345***	-1.112***	-0.260***
					[0.297]	[0.054]	[0.295]	[0.047]
$Dependence_{j,r}$					0.967***	0.901***	0.873***	0.940***
					[0.275]	[0.219]	[0.282]	[0.231]
$np_{i,j,r,t-1}$	42.996***	42.945***	43.243***	42.892***	42.651***	42.682***	42.958***	42.615***
	[0.265]	[0.264]	[0.265]	[0.266]	[0.269]	[0.268]	[0.269]	[0.267]
$np^2_{i,j,r,t-1}$	-29.467***	-29.449***	-29.654***	-29.391***	-29.141***	-29.199***	-29.398***	-29.135***
	[0.267]	[0.267]	[0.267]	[0.268]	[0.271]	[0.270]	[0.271]	[0.270]
$s_{i,j,r,t-1}$	-0.778***	-0.775***	-0.785***	-0.772***	-0.788***	-0.786***	-0.794***	-0.782***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.017]	[0.016]	[0.016]	[0.016]
$cf_{i,j,r,t-1}$	1.527***	1.546***	1.494***	1.531***	1.519***	1.504***	1.464***	1.499***
	[0.180]	[0.179]	[0.182]	[0.179]	[0.184]	[0.183]	[0.185]	[0.184]
$dbt_{i,j,r,t-1}$	-0.133	-0.129	-0.197	-0.114	-0.112	-0.091	-0.183	-0.086
	[0.229]	[0.229]	[0.229]	[0.229]	[0.231]	[0.232]	[0.232]	[0.233]
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.274	0.273	0.274	0.276	0.277	0.276	0.276	0.278
Firms	287,390	289,587	288,814	288,568	280,739	281,702	282,915	281,296
Observations	687,156	693,427	689,757	687,605	670,894	674,021	674,663	669,752
Left − censored	627,377	633,588	629,726	628,288	612,842	615,894	616,424	611,979
Uncensored	59,779	59,839	60,031	59,317	58,052	58,127	58,239	57,773

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,r,t}$ (new product output value / total assets) is a censored variable. We recalculate industry competition based on the eight regional markets. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.10
Modified baseline Euler equations (2.6) and (2.7) of Random-effects Probit estimation for the full sample

	Eq. (2.6)				Eq. (2.7)			
	HHI	EI	LI (PCM)	FI	HHI	EI	LI (PCM)	FI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Competition_{j,t-1}$	-11.608***	-0.393***	-5.215***	-0.311***	-11.574***	-0.063	-1.572	-0.026
	[1.061]	[0.023]	[0.998]	[0.023]	[1.129]	[0.052]	[1.150]	[0.048]
$Competition_{j,t-1} * Dependence_j$					-2.962***	-0.579***	-2.699***	-0.538***
					[0.534]	[0.080]	[0.556]	[0.073]
$Dependence_j$					0.745	1.152**	0.858	1.607***
					[0.530]	[0.459]	[0.532]	[0.493]
$np_{i,j,t-1}$	58.255***	58.148***	59.067***	58.081***	58.821***	58.967***	59.396***	58.495***
	[0.548]	[0.547]	[0.553]	[0.546]	[0.555]	[0.557]	[0.560]	[0.554]
$np^2_{i,j,t-1}$	-45.758***	-45.674***	-46.314***	-45.558***	-46.265***	-46.363***	-46.651***	-45.935***
	[0.499]	[0.499]	[0.504]	[0.498]	[0.508]	[0.510]	[0.511]	[0.506]
$s_{i,j,t-1}$	-1.117***	-1.113***	-1.136***	-1.110***	-1.124***	-1.128***	-1.138***	-1.114***
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
$cf_{i,j,t-1}$	1.733***	1.724***	1.694***	1.729***	1.596***	1.568***	1.594***	1.600***
	[0.215]	[0.215]	[0.219]	[0.214]	[0.219]	[0.220]	[0.222]	[0.218]
$dbt_{i,j,t-1}$	-0.337	-0.372	-0.368	-0.308	-0.423	-0.387	-0.438	-0.369
	[0.272]	[0.272]	[0.277]	[0.272]	[0.277]	[0.279]	[0.280]	[0.277]
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rho	0.412	0.411	0.409	0.411	0.411	0.410	0.409	0.410
Firms	289,733	289,470	288,525	289,484	284,671	283,546	283,627	284,242
Observations	693,736	693,146	688,599	693,038	679,512	673,092	675,328	677,991

Notes: This table reports the marginal effects on the dependent variable $np_{i,j,t}$ of using the random-effects Probit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a dummy variable taking one if firm i in industry j in year t has a positive new product output value (uncensored observations), and zero otherwise (left-censored observations). Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.11

Modified baseline Euler equation (2.6): based on the aggregate industry-level data from 2001 to 2016

	$1 - Herfindahl$		$1 - Lerner$	
	(1)	(2)	(3)	(4)
$Competition_{j,t-1}$	-110.970**	-118.062**	-63.273***	-70.016***
	[50.101]	[52.603]	[50.101]	[19.118]
$s_{j,t-1}$		-44.123***		-48.453***
		[15.117]		[15.023]
$cf_{j,t-1}$		-34.578		46.498
		[60.874]		[59.816]
$dbt_{j,t-1}$		39.372		58.069
		[45.199]		[45.292]
R-squared within	0.261	0.277	0.271	0.286
Prob > F	0.000	0.000	0.000	0.000
Rho	0.453	0.544	0.521	0.476
Industries	50	49	50	49
Observations	749	729	749	729

Notes: This table reports the estimation results of coefficients using the fixed-effects model. The dependent variable ($Innovation_{j,t}$) is an industry innovation index for industry j in year t. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the industry level. Year dummies and industry dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.12

Modified baseline Euler equation (2.6): accounting for the squared competition term

	HHI (1)	EI (2)	LI (PCM) (3)	FI (4)
$Competition_{j,t-1}$	370.532***	-0.228*	-23.368	-0.704***
	[41.841]	[0.135]	[29.198]	[0.152]
$Competition_{j,t-1} * Competition_{j,t-1}$	-199.280***	-0.009	9.659	0.033***
	[21.947]	[0.012]	[15.308]	[0.011]
$np_{i,j,t-1}$	45.014***	45.013***	45.335***	45.123***
	[0.267]	[0.268]	[0.268]	[0.268]
$np^2_{i,j,t-1}$	-31.079***	-31.072***	-31.217***	-31.099***
	[0.271]	[0.271]	[0.272]	[0.271]
$s_{i,j,t-1}$	-0.786***	-0.787***	-0.795***	-0.786***
	[0.016]	[0.016]	[0.016]	[0.016]
$cf_{i,j,t-1}$	1.938***	1.928***	1.868***	1.924***
	[0.177]	[0.177]	[0.178]	[0.177]
$dbt_{i,j,t-1}$	-0.145	-0.165	-0.166	-0.118
	[0.229]	[0.229]	[0.231]	[0.230]
Prob > chi2	0.000	0.000	0.000	0.000
Rho	0.273	0.273	0.270	0.272
Firms	289,738	289,472	288,525	289,486
Observations	693,748	693,152	688,599	693,044
Left-censored	633,493	633,053	628,027	632,955
Uncensored	60,255	60,099	60,572	60,089

Notes: This table reports the marginal effects on uncensored observations using the random-effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.13
Modified baseline Euler equation (2.6) with the interaction term ($Competition_{j,t-1} * IPRs_{p,t-1}$)

	HHI (1)	EI (2)	LI (PCM) (3)	FI (4)
$Competition_{j,t-1}$	-16.044***	-0.520***	-8.176***	-0.428***
	[1.158]	[0.025]	[1.030]	[0.025]
$Competition_{j,t-1} * IPRs_{p,t-1}$	0.824***	0.021***	0.341***	0.017***
	[0.103]	[0.002]	[0.099]	[0.002]
$IPRs_{p,t-1}$	-0.685***	0.005	-0.195**	0.008
	[0.101]	[0.011]	[0.093]	[0.013]
$np_{i,j,t-1}$	44.862***	44.801***	45.180***	44.938***
	[0.267]	[0.279]	[0.267]	[0.279]
$np^2_{i,j,t-1}$	-31.031***	-30.984***	-31.173***	-31.035***
	[0.270]	[0.276]	[0.271]	[0.276]
$s_{i,j,t-1}$	-0.757***	-0.754***	-0.766***	-0.755***
	[0.016]	[0.016]	[0.016]	[0.016]
$cf_{i,j,t-1}$	1.980***	1.983***	1.884***	1.977***
	[0.176]	[0.176]	[0.178]	[0.176]
$dbt_{i,j,t-1}$	-0.165	-0.184	-0.187	-0.144
	[0.228]	[0.229]	[0.230]	[0.229]
Prob > chi2	0.000	0.000	0.000	0.000
Rho	0.272	0.272	0.269	0.271
Firms	289.738	289,472	288,525	289,486
Observations	693,748	693,152	688,599	693,044
Left − censored	633,493	633,053	628,027	632,955
Uncensored	60,255	60,099	60,572	60,089

Notes: This table reports the marginal effects on uncensored observations using the random- effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable, which takes its real value if firm i in industry j in year t has a positive new product output value (uncensored observations), and zero otherwise (left-censored observations). $IPRs_{p,t-1}$ is a province-level index of IPRs protection, which is developed by the National Economic Research Institute (NERI) of China (Fan et al., 2016). Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Ownership dummies, time dummies, industry dummies, location dummies, and constant terms are included in all specifications but not reported. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Rho is the percentage contribution to the total variance of the panel-level variance component in the random-effects Tobit regressions. See Appendix D for definitions of all variables and all classifications. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.14

Modified baseline Euler equation (2.7): accounting for the interaction term ($Competition_{j,t-1} * cf_{i,j,t-1}$)

	HHI (1)	EI (2)	LI (PCM) (3)	FI (4)
$Competition_{j,t-1}$	-12.922***	-0.165***	-0.350***	-0.162***
	[1.073]	[0.044]	[0.020]	[0.041]
$Competition_{j,t-1} * Dependence_j$	-2.471***	-0.463***	-2.518***	-0.432***
	[0.437]	[0.066]	[0.420]	[0.060]
$Dependence_j$	0.450	0.636*	0.474	0.982**
	[0.433]	[0.376]	[0.420]	[0.406]
$Competition_{j,t-1} * cf_{i,j,t-1}$	49.317***	1.299***	15.962***	1.436***
	[7.414]	[0.139]	[4.550]	[0.133]
$np_{i,j,t-1}$	45.114***	45.214***	45.152***	45.196***
	[0.270]	[0.271]	[0.271]	[0.270]
$np^2_{i,j,t-1}$	-31.167***	-31.214***	-31.184***	-31.156***
	[0.274]	[0.276]	[0.275]	[0.275]
$s_{i,j,t-1}$	-0.793***	-0.799***	-0.782***	-0.795***
	[0.016]	[0.016]	[0.016]	[0.016]
$cf_{i,j,t-1}$	-46.666***	-5.487***	-16.851***	-7.827***
	[7.292]	[0.804]	[4.302]	[0.918]
$dbt_{i,j,t-1}$	-0.209	-0.161	-0.220	-0.139
	[0.231]	[0.233]	[0.232]	[0.232]
Prob > chi2	0.000	0.000	0.000	0.000
Rho	0.273	0.271	0.272	0.271
Firms	284,621	283,077	283,400	283,812
Observations	679,341	671,425	676,065	676,513
Left − censored	619,939	612,715	616,968	617,593
Uncensored	59,402	58,710	59,097	58,920

Notes: This table reports the marginal effects on uncensored observations using the random- effects Tobit. The marginal effects are shown as percentages. The dependent variable $np_{i,j,t}$ (new product output value / total assets) is a censored variable. Standard errors (in square brackets) are robust to heteroscedasticity and clustered at the firm level. Year, industry, ownership, and location dummies were included in all models, but their marginal effects are not reported for brevity. Rho denotes the proportion of the total error variance accounted for by unobserved heterogeneity. Prob > chi2 is the joint significance test of parameters, and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. See Appendix D for definitions of all variables and all classifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Appendix A. Structure of the unbalanced panel

Table 2.A1

Distribution of the number of firm-level observations by years

Year	Number of observations	Per cent (%)	Cumulative (%)
1998	122,636	6.26	6.26
1999	120,404	6.15	12.41
2000	125,215	6.40	18.81
2001	135,702	6.93	25.74
2002	150,273	7.68	33.42
2003	171,532	8.76	42.18
2004	261,025	13.33	55.51
2005	256,901	13.12	68.63
2006	284,309	14.52	83.16
2007	329,775	16.84	100.00
Total	1,957,772	100.00	

Appendix B. Average innovation rates and competition intensity across the GB/T two-digit industries in China (1998 – 2007)

Table 2.A2 displays the mean annual innovation rates and competition intensity across 39 GB/T two-digit code industries. We observe that there are 14 industries with an innovation rate higher than the mean value for all industries (7.83%) and these industries are heavy industries or high-tech industries, such as Medical & Pharmaceutical Products (23.0%), Electronic Communication Equipment Manufacturing (20.7%) and Instrument & Apparatus Manufacturing (20.0%). There are 25 remaining industries with an innovation rate lower than the average value for all industries (7.83%), and these industries are light, low-tech or public infrastructure industries, such as Water Production & Supply (0.91%), Electricity, Heat Production & Supply (1.22%) and Gas Production & Supply (1.34%). The patterns for SOEs and private firms are similar. Further statistics on industry competition show that the majority of the industries with a higher innovation rate (over 7.83%) have relatively low competition intensity (lower than the average competition intensity for all industries). We also find that the majority of industries with a low innovation rate (below 7.83%) have relatively high competition intensity (higher than the average competition intensity for all industries). The statistics are in line with Hypothesis 1, according to which there is a negative relationship between competition and innovation.

Table 2.A2
Average innovation rates and competition intensity across GB/T Two-digit industries in China from 1998 to 2007

[GB/T-Two codes] Industry name	Innovation Rate			Competition Intensity			
	Full sample	SOEs	Private firms	HHI	EI	LI (PCM)	FI
[06] Coal Mining & Treatment	2.107	1.720	2.371	98.800	5.814	95.605	7.968
[07] Petroleum & Natural Gas Extraction	4.204	2.574	17.677	90.231	/	97.936	4.290
[08] Ferrous Metals Mining & Treatment	1.598	2.001	1.739	98.604	5.582	93.372	6.523
[09] Non-Ferrous Metals Mining & Treatment	2.174	3.022	2.442	96.472	4.674	92.079	5.618
[10] Non-metal Minerals Mining & Treatment	2.907	6.016	2.674	97.629	4.833	94.270	5.482
[11] Mining of other Minerals	14.729	33.333	29.444	87.939	/	94.458	/
[13] Farm & Side-line Products Processing	4.062	3.448	4.256	98.871	6.007	96.605	6.974
[14] Food Production	7.314	8.116	6.622	97.277	4.638	95.659	5.606
[15] Beverage Manufacturing	9.499	14.379	7.431	96.720	4.665	93.921	5.827
[16] Tobacco Processing	15.906	19.026	50.000	95.616	3.779	91.000	4.632
[17] Textile Industry	6.548	18.283	4.605	99.020	6.336	97.563	7.274
[18] Clothing, Shoes, Hats Manufacturing	3.693	5.071	3.287	99.702	7.596	96.025	8.418
[19] Leather, Fur, Feathers Manufacturing	4.593	14.169	4.830	98.642	5.586	96.309	6.432
[20] Timber Manufacturing	4.440	6.343	4.332	98.246	5.221	96.550	6.013
[21] Furniture Manufacturing	5.529	10.833	6.230	99.061	5.901	95.428	6.652
[22] Papermaking & Paper Products	4.130	9.375	3.373	99.294	6.367	95.921	7.353
[23] Printing Industry	3.951	3.350	3.931	99.110	5.997	93.848	6.818
[24] Cultural Educational & Sports Goods	6.413	25.860	5.972	97.810	5.097	96.348	5.898
[25] Petroleum Processing & Coking	4.379	7.725	2.974	97.503	4.597	99.506	6.804
[26] Chemical Raw Materials & Products	9.207	17.086	8.101	97.913	5.396	95.729	6.560
[27] Medical & Pharmaceutical Products	23.016	29.848	19.898	98.489	5.291	92.015	6.409
[28] Chemical Fibre	11.030	27.792	7.159	95.401	4.209	96.589	5.500
[29] Rubber Products	9.761	31.614	6.564	97.280	4.849	95.951	5.693
[30] Plastic Products	6.089	13.140	5.849	99.252	5.999	95.868	6.801
[31] Non-metal Mineral Products	5.842	7.572	5.180	98.978	6.172	96.362	6.923
[32] Ferrous Metal Smelting & Rolling	5.592	19.008	3.217	98.022	5.344	96.760	7.208
[33] Non-Ferrous Metal Smelting & Rolling	7.318	15.952	5.622	97.157	4.988	97.049	6.172
[34] Metal Products	5.980	15.773	5.327	98.747	5.562	96.214	6.408
[35] Ordinary Machinery	13.546	35.412	9.769	98.148	5.434	95.723	6.363
[36] Special Equipment	17.676	32.785	13.677	96.987	4.598	95.786	5.573
[37] Transportation Equipment Manufacturing	15.661	31.629	9.745	98.099	5.682	96.018	6.940
[39] Electric Equipment & Machinery	13.658	32.830	11.653	98.227	5.408	95.574	6.499
[40] Electronic Communication Equipment	20.653	45.903	18.913	96.515	4.513	95.736	5.952
[41] Instrument & Apparatus Manufacturing	19.990	47.667	17.966	96.186	4.348	95.798	5.277
[42] Handicrafts & other Manufacturing	5.836	13.135	5.669	98.504	5.259	95.699	5.979
[43] Waste Material Recycling Processing	2.997	12.500	3.236	96.442	4.455	95.317	5.282
[44] Electricity, Heat Production & Supply	1.219	1.356	1.332	97.740	5.176	94.455	6.930
[45] Gas Production & Supply	1.341	2.157	13.080	97.803	4.613	99.627	5.772
[46] Water Production & Supply	0.914	0.757	4.486	98.954	5.771	99.020	6.828
Average	7.833	16.117	8.734	97.472	5.291	95.736	6.307

Note: The numbers in square brackets are the GB/T two-digit industry codes assigned by the NBS of China. The innovation rate is defined as the percentage of firms, which have a positive new product output value. The ownership classification is based on the majority (at least 50%) of a firm's total capital paid. Industry competition is measured as the mean of the competition measures based on the 4-digit industry code. HHI, EI, LI (PCM), and FI are four different measures of industry competition based on the Herfindahl Index, the Entropy Index, the Lerner Index (Profit-Cost Margin), and the natural logarithm of the number of firms respectively. All figures are shown as percentages.

Appendix C. Distribution of the number of prefecture-level administrative divisions by innovation rates (1998 and 2007)

Table 2.A3

Distribution of the number of prefecture-level administrative divisions by innovation rates from 1998 and 2007

1998				
Innovation rate \ Region	Coastal	Central	Western	Total
(0 - 5%]	34	35	56	125
(5% - 10%]	41	32	35	108
(10% - 15%]	19	14	17	50
(15% - 20%]	6	17	9	32
(20% - 40.68%]	1	6	9	16
Total	101	104	126	331

2007				
Innovation rate \ Region	Coastal	Central	Western	Total
(0 - 5%]	62	59	85	206
(5% - 10%]	22	30	19	71
(10% - 15%]	7	12	9	28
(15% - 20%]	3	3	5	11
(20% - 45.46%]	7	2	12	21
Total	101	106	130	337

Chapter 2

China's innovation hurdle: competition and finance

Appendix D. Definitions of all variables

New product output value: output value from a firm's new products.

Log (Patent + 1): natural logarithm of the number of a firm's patent applications plus one

R&D expenditure: a firm's expenditure on research and development (R&D) investment.

Competition [HHI]: industry competition level measured with the Herfindahl-Hirschman Index.

Competition [EI]: industry competition level measured with the Entropy Index.

Competition [LI (PCM)]: industry competition level measured with the Lerner Index (Profit-Cost Margin).

Competition [FI]: industry competition level measured with the natural logarithm of the number of firms.

External finance dependence (EFD): industry's dependence on external finance.

Sales: firms' total sales including domestic and overseas sales.

Cash flow: firms' net income plus current depreciation.

New long-term debt issue: the difference between long-term debt in year *t* and *t-1*.

Total assets: the sum of a firm's assets including fixed assets and current assets.

Real total assets: a firm's total assets are deflated using provincial ex-factory producer price indices (PPI) conducted by the NBS of China.

Firm age: the period from the year when the firm was established until the year when the data was recorded.

state shares: a firms' paid-in capitals controlled by the State.

Intellectual property rights (IPRs): a province's score of intellectual property rights protection.

Table 2.A4

Classifications for the degree of financing constraints

Ownership	SOEs Private firms	At least 50% of paid-in capital is state-owned. At least 50% of paid-in capital is privately owned (individuals).
Size	Small Large	The firm's real total assets lie in the bottom half of the distribution of all firms' real total assets belonging to the same ownership group and operating in the same industry in that year. The firm's real total assets lie in the top half of the distribution of all firms' real total assets belonging to the same ownership group and operating in the same industry in that year.
Age	Young Mature	The firm's age lies in the bottom half of the distribution of all firms' age belonging to the same ownership group and operating in the same industry in that year. The firm's age lies in the top half of the distribution of all firms' age belonging to the same ownership group and operating in the same industry in that year.
State Shares	No Yes	The firm has some state shares. The firm has no state shares.
Region	Coastal Central Western	Coastal regions: Liaoning, Tianjin, Beijing, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan; Central regions: Heilongjiang, Jilin, Shanxi, Henan, Anhui, Hubei, Jiangxi, Hunan; Western regions: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

Chapter 3

Do subsidies boost innovation? Evidence from patent filings of industrial firms in China

Using a large panel of industrial firm-level data and patent filings data in China over the period 1998-2008, we find that government subsidies have a positive direct effect on corporate innovation. We confirm the causal effect of subsidies on innovation by using an instrumental variable (IV) estimation and a difference-in-differences (DID) specification. The positive direct effect is enhanced for private firms and financially constrained firms. We also find that the positive direct effect is more pronounced for firms in industries with low external finance dependence (EFD) or high-tech intensiveness, and firms located in cities with low financial development or low foreign direct investment. We further find that subsidies have a greater positive indirect effect on innovation activities of firms without subsidies than firms with subsidies. The paper sheds light on the implications of government subsidies in innovation.

Chapter 3

Do subsidies boost innovation? Evidence from patent filings of industrial firms in China

3.1. Introduction

Since Schumpeter (1911) identified innovation as the critical dimension of economic development, there is long literature that explores the determinants of innovation, including competition (Aghion et al., 2005), institutional ownership (Aghion et al., 2013; Rong et al., 2017), financing constraints (Brown et al., 2009; Brown et al., 2012). Whether government subsidies improve corporate innovation is an academic question that has attracted widespread attention. Yet, empirical findings on the impact of government subsidies on innovation are inconclusive. According to the spillover effect of public goods, government subsidies may facilitate corporate innovation since they can solve the problems of knowledge leakage and market failure in the innovation process (Nelson, 1959; Arrow, 1972; Stiglitz, 1989). However, government subsidies may crowd out firms' inputs into research and development (R&D) and thus impede innovation (Busom, 2000; Wallsten, 2000). Government subsidies for corporate innovation have been a major practice and policy in most countries while the majority of them focus on western economies. This study contributes to the literature by exploring the extent to which subsidies affect innovation in China. Furthermore, we test whether the impact of subsidies on innovation varies across different types of firms, industries, and cities.

After the 1978 reform and open-up, China has experienced its phenomenal economic growth with an average rate of around 10% per year, and thus China becomes from one isolated lagging economy to a highly globalized and the world's second-largest market economy. Alongside China's rapid economic development, China's innovation has made a tremendous improvement in both quantity and quality during the past decades. For the quantity-level of innovation, according to the statistic of the World Intellectual Property Organization (WIPO), China has become the country receiving the largest number of patent applications worldwide since 2011.[64] For the quality-level of innovation, China's latest ranking is 17th in the report of 'Global Innovation Index 2018' published by the WIPO, which is the first time that China rides to the top 20 countries of the global innovation index.[65] The ranking of China is the highest among all developing economies, and even higher than that of some developed economies such as Canada (18th), Australia (20th), and Spain (28th). In addition to the innovation outputs, China's innovation input has also increased significantly. According to the OECD statistics, China's gross domestic spending on R&D is 462,578 million US dollars in 2018, which is higher than that of other OECD members only except the US (551,518 million US dollars).[66] China is one of the few low or low-middle income countries whose R&D intensity (measured by the ratio of R&D expenditure to GDP) has risen by over 1%. Although China's innovation has greatly improved in the decades, it still faces some considerable challenges such as weak intellectual property protection (IRP), overwhelming dependence on foreign technology, low input-output efficiency. In recent years as China is facing several bottlenecks in its economic growth,[67] the Chinese government has realized innovation especially indigenous innovation would become the main driver for reversing China's current economic slowdown. The government-led emphasis is being gradually placed on the in-depth development of China's innovation through different aid programmes. For example, in 2006 the State Council of China employs a strategy called 'National Program for Medium- and Long-term Scientific and Technological Development' (hereafter NPMLT), which aims at promoting China's

[64] *The Economist*, 'How innovation is China? Valuing patents', Jan. 5th, 2013.

[65] The report of 'Global Innovation Index 2018' could be browsed through the website address: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2018.pdf.

[66] The data source for the gross domestic spending on R&D is from the OECD website, available at: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm.

[67] China's economy is now facing some difficulties, such as soaring labour costs, high staff turnover, and saturated infrastructure investments. From 1978 to 2014, China's Gross Domestic Product (GDP) maintained a high growth rate of around 10% per annum, while after 2014 its growth has slowed below 7% per annum.

innovation.[68] In 2015, the Chinese central government puts forward a strategic plan of 'Made in China 2025' to drive innovation.[69]

As one important economic intervention tool implemented by governments to achieve economic targets, subsidies have been explored in academic areas such as production efficiency (Bagwell & Staige, 1989; Bagwell & Staige, 2006), firm value or firm performance (Lee et al., 2014; Lim et al., 2018). Due to the unique government-influenced economic model in China, governments (including central and local) still maintain enormous influence over enterprises through policy instruments such as subsidies. Specifically, governments can support their favoured enterprises or industries by allocating subsidies. Government subsidies are considered as one of the most important financial sources for Chineses firms (Allen et al., 2005).[70] Thus, to explore the role of subsidies in China's rapid economic rise during recent decades is increasingly important since there is a global debate about whether subsidies could give an unfair advantage to Chinese firms to compete with their foreign counterparts (Godement et al., 2011; Hormats, 2011; Fang & Walsh, 2018). Given the importance of innovation for China's economic growth and government subsidies in innovation has become a top national innovation strategy, the impact of subsidies on innovation deserves more in-depth studies in China.[71] Besides, there has been little systematic research on how subsidies affect innovation in

[68] The NPMLT strategy has three objectives that could be summarized as follows: first, china committed to increasing its ratio of R&D expenditure to GDP to 2.50% in 2020; second, China committed to stimulate its indigenous innovation and reduce foreign technology dependence; third, corporations would become the main driving forces of innovation. The state council also issued a list of follow-up policies implemented by government ministries and agencies at all levels for supporting the strategy.

[69] In May 2015, the Chinese Premier Li Keqiang and his cabinet issued the plan 'Made in China 2025', which aims to help China move from being the world's 'factory' (producing cheap and low-quality goods) and move to produce higher-value products and services.

[70] Allen et al. (2005) suggest that the four important financial sources for Chinese firms are bank loans, firms' self-fundraising, foreign direct investment, and government subsidies.

[71] According to Fang et al. (2018), government subsidies account for 22% of Chinese firms' R&D expenditures.

emerging economies. Our paper can enrich the understanding of the role of subsidies in innovation by examining the link between government subsidies and firms' innovation activities in China, the largest emerging market. observations covering

In this study, we examine the effect of subsidies on innovation by using a huge unbalanced panel of 2,373,488 observations covering 663,699 large and medium-sized enterprises distributed in 31 provincial regions and 40 GB/T two-digit industries over the period 1998-2008. We find a significant and positive direct effect of subsidies on firms' innovation activities. To mitigate the potential problem of endogeneity, we first employ the instrumental variable (IV) method by using city-level fiscal revenue and the median value of government subsidies in each year-city-industry-ownership cluster as the instrumental variables for subsidies received by firms from governments. We further employ lagged values of government subsidies as the instrumental variable for a robustness test. Second, to provide clear identification of the causal effect of subsidies on innovation, we implement a difference-in-differences (DID) method based on a subsample of firms in Suzhou (the most economically developed prefecture-level city in China). Specifically, one county-level city of Suzhou, Zhangjiagang, revised its patent subsidy policies in 2006 while other county-level cities of Suzhou did not make any revisions in the meantime. In this quasi-natural experiment, we find that in response to this exogenous patent subsidy policy, affected firms improve innovation more than firms not directly affected by the policy revision. Third, to mitigate potential omitted variables that affect firms' innovation activities, we add the contemporaneous terms of independent variables into our regression models. Fourth, to overcome concerns about measurement error of firms' innovation activities, we also use firms' new product output value as a measure of firms' innovation output and R&D expenditure as a proxy of firms' innovation input. These results remain qualitatively the same.

To further enhance robustness, first, considering that patents have different levels of quality, we only use the number of firms' invention patent applications to proxy firms' innovation output since invention patents represent good-quality patents. Second, we employ the Zero-inflated Poisson method to estimate because the number of patent applications per firm is a counting variable that has lots of zero outcomes. Third, we standardize the independent variables in regressions by using the natural logarithm of firm-level financial variables. Fourth, we choose an alternative sample excluding the data in the year 2008 to estimate due to the data limitation in the year 2008. All robust estimation results keep qualitatively unchanged.

Furthermore, we find that government subsidies have a stronger positive direct effect on innovation for private firms compared to SOEs. We also find that the positive direct effect of subsidies on innovation is more pronounced for firms with more financial constraints compared to their financially healthier counterparts. We further explore whether the impact of government subsidies on innovation varies across industries and cities. At the industry-level, we find that the positive direct effect of subsidies on innovation is weaker for firms in industries with higher external finance dependence (EFD) but stronger for firms in industries with high-tech intensiveness. At the city level, the positive direct effect of subsidies on innovation is weaker for firms in cities with higher financial development and higher foreign direct investment (FDI). We further find that subsidies have a spillover effect on innovation activities of firms without subsidies.

Our paper contributes to the literature in the following ways. First, it contributes to the literature on the effects of subsidies on innovation. To the best of our knowledge, our paper is the first to investigate the direct effects and indirect effects of government subsidies on firms' innovation activities in China based on a large number of industrial firms which are mainly unlisted. Prior studies have investigated the effects of subsidies on innovation while the majority of them focus on developed economies (Nelson, 1959; Arrow, 1972; Stiglitz, 1989; Busom, 2000; Wallsten, 2000; Almus & Czarnitzki, 2003; Kleer, 2010; Bronzini & Piselli, 2016). However, as the largest emerging economy with a strong government role, China's experiences are instructive. Besides, previous papers exploring the effect of subsidies on innovation in China focus on the data of listed firms (Boeing, 2016), while listed firms cannot fully reflect China's economy.[72] Our paper is distinct from but also complementary to the literature by exploring a large panel of industrial firms (consists largely of SMEs and 95% of which are unlisted). Second, our paper contributes to the literature on the effects of subsidies on firms' performance. Several papers have studied the factors that could be impacted by subsidies in China, such as firm value (Lee et al., 2014), corporate social responsibility (Lee et al., 2017), firm performance and the cost of debt (Lim et al., 2018). Using a large panel of industrial firms which are mainly unlisted, our paper explores the role of subsidies on innovation in China. Third, our paper contributes to the literature on innovation. Some studies have examined various factors affecting innovation in China, including financial constraints (Guariglia & Liu, 2014), institutional ownership (Rong et al., 2017), input tariff liberalization (Liu & Qiu, 2016) and total factor productivity (Boeing et al., 2016). Since subsidies are one of the main financing sources for China's firms (Allen et al., 2005), it is important to explore innovation from the perspective of subsidies. Fourth, due to the 'lending discrimination' and the imbalance of regional economic development in China, for the first time, we extend the existing research by linking with the heterogeneity on firms, industries, and cities.

The rest of the paper is organized as follows. In Section 3.2, we introduce the background of China's patent applications and government subsidies. In Section 3.3, we illustrate our theoretical motivation. In Section 3.4, we describe our datasets. In section 3.5, we

[72] Generally, firms that can go public are firms with relatively good qualifications, standard management, and strong profitability. Thus, listed firms are less representative of all china's enterprises.

explain our estimation specifications variable measures. In Section 3.6, we show summary statistics and discuss empirical results. In Section 3.7, we make some tests for alleviating endogeneity issues. In Section 3.8, we make further tests of heterogeneity on firms, industries and cities. We also test the indirect effect of subsidies on innovation in the section. In Section 3.9, we draw some conclusions.

3.2. Background of China's patent applications and government subsidies

3.2.1. China's patent applications

With the China economy on a firmer footing in recent decades, China's patent filings also have experienced a dramatic growth rate. For example, the report of 'World Intellectual Property Indicators 2018' shows that the number of China's patent filings increased from 18,700 in 1995 to 1,381,594 in 2017 with an average annual rate of 23%.[73] The report also admits 'China remained the main driver of global growth in filings', which could be reflected by that China's patent filings account for 43.6% of patent applications worldwide in 2017 and experience a growth rate of more than 10% each year since 2010. Although patent applications in China started late and from a small base, China has become the world leader receiving patent applications, outpacing Europe and South Korea in 2005, Japan in 2010, and the U.S. in 2011. The jump in China's patent applications has therefore drawn a lot of attention from both economists and innovation scholars. For example, Hu and Jefferson (2009) explore factors that account for China's recent patent explosion, including foreign direct investment (FDI),

[73] The report of 'World Intellectual Property Indicators 2018' could be browsed via: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2018.pdf. Since China revised its statistics method of patent applications in 2017 (China counts all patent applications received before 2017 while starting from 2017 it only counts applications for which the office received with necessary application fees)

amendments to the patent law, and ownership reforms. Li (2012) suggests that patent subsidy programs implemented by each provincial region have played an essential role in the explosive growth of Chinese patenting based on publicly available data. Some papers also find negative factors of China's innovation, such as Liu and Qiu (2016) that find a negative relationship between a drastic input tariff liberalization and corporate innovation.

Fig. 3.1 shows clearly the growing trend of the number of total patent applications to the State Intellectual Property Office (SIPO) of China since 1985 when the patent system was first implemented in China. According to the statistics, the number of total patent applications increased from only 18,509 in 1986 to 3,697,845 in 2017 with an average annual growth rate of 19.1%.[74] Specifically, we find that patent applications grew rather modestly until the end of the 1990s, while after 2000 especially 2002 have surged dramatically (except 2014), which may be explained by the benefits of technology embedded in imported inputs caused by China's entry into the WTO in December 2001. Amendments to patent law in 2000 also make a huge contribution to the upsurge in the new century. Also, we find that the SIPO receives the bulk of its patent applications from domestic innovators rather than foreign innovators. Although domestic and foreign applications both show growth trends, their growth rates are different. Specifically, domestic applications experienced excessive growth from 13,680 in 1986 to 3,536,333 in 2017, while foreign applications had a relatively sluggish growth from 4,829 in 1986 to 161,512 in 2017. Thus, the difference in the number of applications between domestic and foreign increased from 8,851 in 1986 to 3,374,821 in 2017. The explosive surge of domestic applications may be interpreted by consistent policies issued by China's

[74] The data in 1985 is recorded from 1st April 1985. Thus, we observe the development trend of China's patent applications from the year 1986 rather than the year 1985. This also applies to the next description of Fig. 3.2.

government for stimulating indigenous innovation, such as the patent law amendments in 2008, which can encourage indigenous innovation.

[*Insert Figure 3.1 here*]

There are three types of patents granted by the SIPO: invention, utility model, and design. The three types of patents are different in applicable targets, protection period, and approval procedures.[75] Among these three kinds of patents, invention patents are regarded as major innovation patents with high quality as they have the most difficult examination requirements. Fig. 3.2 shows the proportion of the three types of patent applications in China during the period from 1985 to 2017. We can find that the proportion of invention patent applications first had a downward trend from 43.27% in 1986, while after the patent law amendment in 1992 it presented a growth trend to 37.36% in 2017 although the growth trend fluctuated slightly. During the period, the proportion of utility model patent applications first decreased before 2007 and then increased, while the proportion of design patent applications did the opposite (increased before 2007 and then decreased). We also can find that during the period the proportion of invention patent applications rarely outpace 40% (except the year 1985 and the year 1986), which is against the sum of the proportion of utility model patent applications and the proportion of design patent applications always being higher than 60%. The findings suggest although invention patent applications play an increasingly important role in the application system of China's patents, the overall quality of China's patent applications is still not high.

[*Insert Figure 3.2 here*]

[75] The detailed differences of the three types of patents are described in Appendix A.

3.2.2. China's government subsidies

Subsidies are a form of financial aid or support granted by the government or a public body and extended to a microeconomic sector (or institution, business, or individual) to promote economic and social policy (Myers, 2001). Government subsidies can be divided into various types based on targets, such as production subsidies, import/export subsidies, employment subsidies, R&D subsidies, etc. As a form of economic intervention, subsidies are inherently contrary to the free market's demands. However, according to Schwartz and Clements (1999), there are at least three reasons why governments still apply subsidies as a policy instrument in the process of economy-control. First, governments could use subsidies to offset various market imperfections because the free market's 'invisible hand' cannot always allocate resources most efficiently. Second, governments could use subsidies to gain economies of scale in production when important sectors are too small in scale to compete with their larger and more mature counterparts in the market. Third, governments could employ subsidies to achieve social policy objectives, such as a fairer distribution of consumption or income.

As one of the four main financing sources (Allen et al., 2005), subsidies play an important role in the surge of China's economy during the past decades. Since 1953 when China's central government issued its first 'Five-year' plans to manage its industrial development, government subsidies in China are prevalent and persistent. The 'Five-year' plans of different periods issued by China's central government show targeted products, enterprises, and industries that governments need to support in different periods. Subsidies are one of the most important financial tools to reflect administrative support. For example, more subsidies are allocated by governments to the enterprises in some strategic emerging industries in the 13th Five-year plan covering 2016 to 2020, such as information and communication technology, aerospace hardware, new energy fuelled vehicles, and marine engineering equipment.

Besides the central government, local governments also have the incentives to subsidize firms caused by two reasons. First, since the reform and open-up policy in 1978, China's central government has been delegating the power on subsidy allocation to local governments. The decentralization makes that local governments have considerable discretion in determining the number of subsidies allocated to corporations. Second, the most important indicator for evaluating local government officials' performance is the economic performance (GDP) of their respective areas. The evaluation performance mode, as well as the decentralization, lead to severe competition among local officials to promote economic development. Thus, local officials are keen to assist firms in their respective areas by granting subsidies.

For China's innovation (i.e. patent) subsidy policies, since 1999 Shanghai (the city with the largest economy in China, administratively equal to a province) implemented China's first patent subsidy policy to promote local enterprises' patenting activities, until 2007 most of the provinces have launched similar programs and many prefecture-level cities have their subsidies for patent applications (Li, 2012).[76] Government subsidies come in various distribution forms, and all seven categories of them given by Schwartz and Clements (1999) have been

[76] According to China's constitution, cities are divided into three administration levels: 4 municipalities (Beijing, Tianjin, Shanghai, and Chongqing) are first-level (province-level) administrative divisions and directly governed by the central government. The four cities are administratively to other 30 province-level administrative divisions (including Hong Kong, Macao, and Taiwan); prefecture-level cities including 15 sub-provincial cities are secondary-level (prefecture-level) administrative divisions and directly governed by the provincial government. These prefecture-level cities are ranked below province-level while above county-level in the administrative structure of China; county-level cities are third-level (county-level) administrative divisions and governed by the prefecture-level city government. Provincial governments directly govern a few county-level cities. The county-level cities are the lowest-ranking cities in China. According to the *China Statistical Yearbook* 2018 (http://www.stats.gov.cn/tjsj/ndsj/2018/indexch.htm), by the end of 2017, there are totally 4 municipalities, 294 prefecture-level cities and 363 county-level cities in China.

implemented to facilitate innovation in China.[77] Some policies offer a fixed amount of reimbursement to firms for patent applications, regardless of the actual costs or whether the application is granted. Some policies provide subsides with a cap based on applicants' actual out-of-pocket expenses. Some policies pay a portion of application fees to applicants and award a prize (usually a much larger amount) for applications granted. For example, the State Council of China in 1999 approved the 'innofund program,' which is a special government R&D program to support innovation activities of small and medium technology-based enterprises (SMTEs) by appropriation, interest-free bank loans, and equity investment.

Due to the various distribution forms of subsidies, the total amount of government subsidies is potentially unobservable because a fraction of subsidies granted is in the form of non-monetary supports (in other words, indirect grants). A bias is likely to appear since subsidies are underreported in firms' financial statements. In China's context of the study, we focus on the observable forms of government subsidies that are recorded in firms' income statements.

3.3. Theoretical motivation

It is challenging to empirically test the impact of government subsidies on corporate innovation. There seems no consensus among prior research. A considerable number of scholars (Nelson, 1959; Arrow, 1972; Stiglitz, 1989; Görg and Strobl, 2007; Aerts & Schmidt,

[77] Schwartz and Clements (1999) define the seven categories of government subsidies as: 'direct government payments to producers or consumers (cash subsidies or cash grants); government guarantees, interest subsidies to enterprises, or soft loans (credit subsidies); reductions of specific tax liabilities (tax subsidies), government equity participations (equity subsidies); government provision of goods and services at below-market prices (in-kind subsidies); government purchases of goods and services at above-market prices (procurement subsidies); implicit payments through government regulatory actions that alter market prices or access (regulatory subsidies)'.

2008) suggest that government subsidies have a positive effect on corporate innovation. On the contrary, some scholars (Busom, 2000; David et al., 2000; Wallsten, 2000; Acemoglu et al., 2018) argue that government subsidies affect corporate innovation negatively.

On the one hand, there exists considerable evidence to show that government subsidies have a positive impact on corporate innovation. One research strand suggests that government subsidies could mitigate the uncertainty risk associated with innovation and have more incentives to innovate. Due to the spillover effect or knowledge leakage caused by R&D projects, innovators could not reap the full benefits of innovation and then weaken firms' R&D incentives (Clarysse et al., 2009). This might subsequently lead to a market failure problem that R&D input cannot reach the optimal level (Arrow, 1972; Stiglitz, 1989). Besides, compared to other investments, R&D projects require a demand for high inputs and a long-term investment cycle, which could result in higher costs of external financing. Government subsidies could stimulate firms' innovation motivation due to the following reasons. First, subsidies can reduce the marginal cost and diversify the uncertainty risk of R&D projects (Almus & Czarnitzki, 2003; González & Pazó, 2008) by serving as a supplement to the innovation funds needed by firms (Tether, 2002). Second, government subsidies can reduce the problem of information asymmetry between firms and external investors by providing a positive signal of the firm's quality. Specifically, external investors cannot fully know the real information on R&D projects. Obtaining government subsidies for a firm may signal to market investors that the firm has a greater probability of owing projects with high quality and low risk (Lerner, 1999; Feldman & Kelley, 2006; Kleer, 2010). Consequently, firms receiving government subsidies are more likely to raise more external funds for innovation. Hence, many scholars suggest that government subsidies are a supplement to innovation funds and have a positive effect on firms' innovation activities.

On the other hand, another research strand holds that subsidies hurt firms' input into R&D projects and thus play a discouraging role in firm innovation. Some scholars suggest that after obtaining subsidies from governments, due to managerial myopia (Stein, 1988), firms' managers may invest these funds into projects with a short-term investment cycle to pursue more short-term profits rather than long-term projects such as R&D (Lundstrum, 2002). Subsidies may fail to play their expected role as a supplement to innovation funding at this condition since subsidies would be moved to more short-term projects whose funds are not fully covered. Thus, firms receiving subsidies from governments create a crowding-out effect on their innovation inputs (Yu et al., 2016). Also, because firms' capital risk would be lower as R&D inputs decrease, firms with more subsidies tend to decrease more inputs into R&D and invest in more projects with short-term profits. The crowding-out effect of subsidies on innovation will become more obvious (Boeing, 2016). Therefore, some scholars argue that government subsidies fail to add more innovation funds and hurt firms' innovation activities.

3.4. Data

This paper relies on a combined database that covers the patent data of the State Intellectual Property Office (SIPO) and the firm-level data of the National Bureau of Statistics (NBS) of China.

3.4.1. SIPO patent data

The first data source for firms' patent applications is the SIPO patent data (http://www.sipo.gove.cn), which is available since 1985 when the patent system was established in China. The SIPO dataset provides detailed information on all published patent applications, including patent application number, patent application date, applicant's names and addresses, patent's international patent classification (IPC), i.e., whether the patent is applied as an invention patent, a utility model patent, or a design patent. The data is the most comprehensive coverage of patent information, and thus could be used in exploring China's innovation. However, due to the difficulties in integrating such data with other firm-level data since the SIPO patent data nearly has no same common identifier with other datasets, academic papers using Chinese patent data are still sparse. Some papers (Dang & Motohashi, 2015; Liu & Qiu, 2016) choose the official Chinese names of patent applications recorded in the SIPO patent data to merge such data with the NBS firm-level data used in the study. However, this matching method still has some drawbacks since the names of firms listed in the datasets may not be fully consistent. Specifically, first, in the NBS firm-level data, the recorded variable of firms' official names has many obvious errors.[78] Second, one firm's name could change in the NBS firm-level data but the corresponding applicant firm probably does not timely update in the SIPO patent data or vice versa. Thus, if we directly link the SIPO patent data with the NBS firm-level data by using firms' names, there are potential estimation bias arising from the matching step. Fortunately, He et al. (2018) have created a matching algorithm that fits with the SIPO patent data and the NBS firm-level data from 1998 to 2009.[79] They processed the SIPO patent data and found the corresponding legal person codes of each patent applicant. Thus, we can merge the SIPO patent data processed by He et al. (2018) with the NBS firm-level data by using firms' legal person codes. The merging process is described in Section 3.4.3.

3.4.2. NBS firm-level data

The second data source for firm-level financial information is the Annual Survey of Industrial Enterprises over the period 1998-2008, which is drawn from the annual accounting

[78] For example, we see many problematic names such as '鄂鄂州市隆昌合金钢有限责任公司' (the second 鄂 is redundant and must be a data entry error) and 'S 试第星旆嵋_铣' (the firm name is a total error messed up).

[79] The processed database could be found in He, Z.-L., Tong, T., Zhang, Y. & He, W. Harvard Dataverse http://dx.doi.org/10.7910/DVN/QUH8KT (2017).

reports conducted by the National Bureau of Statistics (NBS) of China.[80] Thus, the census data is called NBS firm-level data and the most comprehensive firm-level dataset that spans the population of large and medium-sized firms in China. These firms are either state-owned enterprises (SOE) or non-SOE with annual main business income (i.e., sales) above 5 million Chinese yuan (approximately 680,000 US dollars, according to the official 2008 exchange rate).[81] The data covers roughly 165,000 businesses in 1998 to around 450,000 in 2008 as more enterprises are added during the period. All firms in the dataset are distributed in 39 mining, manufacturing, and public utilities and across all 31 provinces or provincial administrative units (except Hong Kong, Macao, and Taiwan), representing the broad Chinese economy. The dataset features detailed firm characteristics such as official names, locations, industry codes as well as most items of each firms' financial performance every year, including total assets, total liabilities, main business sales, net income, accumulated depreciation, etc. The original sample for the period 1998-2008 contains 2,640,143 observations.[82] Additionally, the data has an advantage in constructing a panel with its unique legal identifier known as the legal person code (*fa ren dai ma*) to each firm (Chang & Wu, 2014).[83] The data has been explored in studies

[80] Actually, now the dataset has been updated to 2013. However, we have to stop the data until 2008 due to some reasons as follows. First, some key variables are lost after 2007 such as the current-year depreciation that is lost during the period 2008 to 2010, while current-year depreciation is used for calculating cash flow which is one control variable in our regression models. Since in our baseline model all independent variables are lagged by one year, we can choose the latest data until 2008. Second, the patent data for matching with NBS firm-level data is processed by He et al. (2018) until 2010. Third, in 2011 the China NBS adjusts the threshold of 'above-scale' enterprises for this dataset by increasing annual sales from 5 million Chinese yuan to 20 million Chinese yuan. Fourth, the financial crisis in 2008 potentially could make an estimation bias. Based on the above reasons, we have to choose the latest data until 2008.

[81] The firms with annual sales of more than 5 million Chinese yuan are referred to 'above-scale' firms, and thus the dataset is also called 'above-scale' industrial enterprise database.

[82] In order to enhance the data reliability, we compare the NBS firm-level data with the records of the *China Statistical Yearbook*. The detailed description could be viewed in Appendix A.

[83] We do not choose firms' names to construct the panel data since firms could change their names frequently. According to China's Company Registration Rules, the legal person code of one firm is unique nationwide and

of economy and finance on serval topics: competition (Cai & Liu, 2009; Aghion et al., 2015), financial constraints (Ding et al., 2013; Guariglia & Liu, 2014), foreign direct investment (Wang & Wang, 2015; Lin & Ye, 2017) and innovation (Hu & Jefferson, 2009; Liu & Qiu, 2016)

Before the construction of the combined data with the SIPO patent data, we process the NBS firm-level data to secure data quality. First, we supplement 408 observations' legal person codes which are less than nine digits to nine digits by and capitalize all English letters in the legal person code of 5,834 observations in the dataset to eliminate the influence of data collection error.[84] Second, we remove 5,838 observations without legal person codes and 641 observations with duplicated legal person codes, as these observations could not be used to construct the panel data.[85] Third, since China's government revised the 'National Industries

would not change after the registration of its legal entity even if it has adjusted its name and business nature. Occasionally, firms change their legal person code as firms' ownership has changed, which may be caused by restructuring, joint ventures, mergers and acquisitions, etc. For this situation, these firms generally change their legal entity. Thus, we treat only firms with different legal person codes are different firms and use firms' legal person codes to construct the panel data.

[84] First, in the dataset, 408 observations in 2008 have a legal person code of fewer than nine digits. We manually check them and find that this is a data collection error. If we use figure 0 to complement these observations' legal person codes to nine digits, we can observe that some of these 408 observations in 2008 are the same firms as observations with the corresponding complemented legal person codes in previous years. For example, the observation with the legal person code of '9316247' in 2008 actually is the same firm as the observation with the legal person code of '009316247' in 2007. Second, we also find that this is a data collection error for 5,834 observations with lowercase English letters in legal person codes. After capitalizing all English letters in the legal person code of these observations, we find that observations with the adjusted legal person codes in other years are the same firms as those 5,834 observations. For example, the observations with the legal person codes of 'x20723214' in 2005, 2006 and 2007 are the same firm as the observations with the legal person codes of 'X20723214' in 2004 and 2008.

[85] Some different firms share the same legal person code (probably due to statistical errors) and we cannot distinguish exactly which one of the various observations with the same duplicated legal person code is reliable. The fraction of these observations is quite low, roughly 0.024%, and thus we delete all observations with duplicated legal person codes in order to construct the panel and ensure data reliability.

Classification' in 2002 to keep consistent with the WTO regulation in 2001, we adjust the sector codes for firms before 2002 to keep the sector codes consistent during the sample period.[86] We delete 7,646 observations in the industries transferred from manufacturing sectors and in the industries that disappeared in the scope of manufacturing sectors after the classification revision in 2002, as firms in these industries could not keep consistent during the sample period. After the industry-matching procedure, we use the updated industry codes to construct industry dummy variables in regression models. Fourth, we drop 253,108 observations with annual sales of less than 5 million Chinese yuan to avoid the interference of no 'above-scale' enterprises.[87] Fifth, we drop 218 observations from the dataset by following the basic rules of the Generally Accepted Accounting Principles (GAAP). Specifically, observations whose total fixed assets are greater than total assets; liquid assets are greater than total assets; current depreciation is greater than accumulated depreciation are taken out of our sample.

3.4.3. Merging SIPO patent data with NBS firm-level data

We construct our unique dataset by linking the SIPO patent data processed by He et al. (2018) with the NBS firm-level data. Specifically, for the SIPO patent data, we calculate the number of each firm's all patent applications (including invention, utility model and design) every year as the measure of firms' innovation output, and then we merge the calculated innovation proxy with the NBS firm-level data through firms' legal person codes. After merging, we find that only approximately 3.42% of observations in the NBS firm-level data

---

[86] The Chinese description of the 'National Industries Classification' revision in 2002 could be viewed via: http://www.stats.gov.cn/tjgz/tjdt/200207/t20020711_16330.html. The detailed information on China's industry codes and the adjustment in 2002 are shown in Appendix B.

[87] We have discussed that the dataset also records SOEs with annual sales of less than 5 million Chinese yuan. Additionally, in 2004 and 2008, all industrial firms are required to participate in the China NBS survey.

have patent applications, suggesting that the participation rate of applying patents for Chinese firms is low.

To obtain a clear panel, we trim observations in the one per cent tails of each of the firm-level continuous regression variables to control for the potential influence outliers.[88] All financial variables are deflated by using the provincial-level Producer Price Index (PPI) of each year during the sample period (1998 - 2008) conducted by the NBS.[89] After all adjustments, we finally get a large unbalanced panel data of 2,373,488 observations covering 663,699, mainly unlisted firms for the period 1998-2008.[90]

Based on our adjusted huge unbalanced panel data, we observe patent applications of China's firms from different perspectives (years, regions, and industries). Fig. 3.3 and Fig. 3.4 respectively show the development trends of the participation rate of patent applications for firms and the number of patent applications per 1,000 firms in China during the period 1998 – 2008. On the one hand, we can find that from 1998 to 2008, China's firms show an increase in the enthusiasm of applying for patents. Specifically, for the full sample, the participation rate of patent applications increases from 2.10% in 1998 to 4.34% in 2008. There is also an increasing trend for the number of patent applications per 1,000 firms from 73.67 in 1998 to 373.33 in 2008. On the other hand, although firms' patent applications in China have shown obvious growth trends in the decade, we find that the level of China's patent applications is

[88] The number of patent applications is a firm-level discrete variable and only less than 4% of the observations have patent applications. Additionally, because we employ the natural logarithm of the number of patent applications, the influence of discrete characteristics could be avoided to some extent. Thus, we do not winsorize the variable of innovation output of $log\ (Pat_{i,t} + 1)$ in our regressions.

[89] The information on the provincial-level PPI could be searched on the NBS website (http://data.stats.gov.cn/).

[90] Appendix A shows details of the structure of the unbalanced panel. Additionally, because the data in 1998 and 1999 are used to construct lagged values in regression models. To enhance compatibility with the data in our regression estimations, in Table 3.2 of summary statistics we only summarize the data in our regression models during the period from 2000 to 2008.

still not high, which can be reflected by the low participation rates of patent applications (never exceed 5%). The increase in firms' enthusiasm for applying patents is possibly interpreted by the policies of promoting innovation issued by Chinese governments, and the low participation rates of Chinese firms' patent applications may be caused by that Chinese firms' face R&D capital constraints.

[*Insert Fig. 3.3 here*]

[*Insert Fig. 3.4 here*]

Fig. 3.3 and Fig. 3.4 also compare SOEs and private firms in China.[91] It is clear that compared to private firms, SOEs have a higher level of patent applications over the whole sample period, no matter in the participation rate of patent applications or the number of patent applications per 1,000 firms. Specifically, the participation rate of patent applications for SOEs and private firms respectively is 2.96% and 1.69% in 1998. Although the rate for SOEs and the rate for private firms grow separately to 7.32% and 3.46% in 2008, we can find that the difference in participation rates between SOEs and private firms rises from around 1.27% in 1998 to 3.86% in 2008. It also can apply to the number of patent applications per 1,000 firms and the gap of the numbers between SOEs and private firms increases from almost 22.97 to 561.51. A reasonable explanation for the enlarged gap is that SOEs can expand their advantages in applying for patents by enjoying the privilege of cheap loans from banks dominated by state capital or easily get support from governments such as subsidies. Besides, the relatively weak China's IRP possibly limits private firms' patent applications since they have to protect

[91] We use the percentage of paid-in capitals to identify firms' ownership types. If a firm's at least 50% of paid-in capitals are owned by the state, it is an SOE; if a firm's at least 50% of paid-in capitals are owned by individuals, it is a private firm.

business interests, while SOEs can take advantage of their good connections with governments to fully ensure their benefits.

Fig. 3.5 and Fig. 3.6 respectively show the snapshots of the average participation rate of patent applications for firms and the average number of patent applications per 1,000 firms across prefecture-level administrative divisions in China during the period 1998 - 2008.[92] We can find that cities in coastal regions have a higher level of patent applications than cities in central and western regions, no matter in the participation rate of firms' patent applications or the number of patent applications per 1,000 firms. It keeps consistent with the conventional view that patenting activities are positively related to economic development.[93] Specifically, we find that more than two-thirds of the cities in coastal regions ((38+31)/101=68.32% and (39+29)/101=67.33%) have higher values than the median values of the average participation rates (1.87%) and the average number (62.71) across cities. However, the proportions of cities in central regions and western regions owning values greater than the median values of the average participation rates (1.87%) and the average number (62.71) across cities are all below

[92] There are totally three main administration levels in China. We have introduced in Note 14 that four municipalities (Beijing, Tianjin, Shanghai, and Chongqing) are administratively equivalent to other 30 province-level administrative divisions (including Hong Kong, Macao, and Taiwan). The second level is prefecture-level administrative divisions (prefecture-level cities, areas, autonomous prefectures or leagues). The third level is county-level administrative divisions (districts, county-level cities, counties, autonomous counties, banner or autonomous banner). According to the *China Statistical Yearbook* 2018, by the end of 2017, there are totally 34 province-level administrative divisions (excluding Hong Kong, Macao, and Taiwan), 334 prefecture-level administrative divisions and 2,851 county-level administrative divisions in China. Our maps of Figure 5 and Figure 6 are based on 4 municipalities and 334 prefecture-level administrative divisions. Hong Kong, Macao and 21 cities in Taiwan are included in the maps, but they miss the data records.

[93] The economic development among regions in China is not balanced. Coastal regions are the most important areas in China's economy. For example, according to the 2018 *China Statistical Yearbook*, China's gross domestic product (GDP) is 82,712.77 billion yuan and the sum of GDP for 11 provinces in coastal regions (excluding Hong Kong, Macao, and Taiwan) is 47,124.47 billion yuan that is 56.97% of the country's GDP. In contrast, the sum of GDP for 8 provinces in central regions and sum of GDP for 12 provinces in western regions are only 20,733.38 billion yuan and 16,856.16 billion yuan that are respectively 25.07% and 20.38% of the country's GDP.

half. The findings can suggest that the development level of patenting activities in coastal regions is better than that in central and western regions. The detailed data of the distribution of the number of prefecture-level administrative divisions for Fig. 3.5 and Fig. 3.6 are shown in Appendix E.

[*Insert Fig. 3.5 here*]

[*Insert Fig. 3.6 here*]

3.5. Estimation specifications and variable measures

We choose a modified Euler equation that is first employed to test the presence of financial constraints on investment (Whited, 1992; Bond et al., 2003). As a dynamic structural model, the Euler equation model has the advantage of controlling expected future profitability. Thus, financial variables in the regression do not pick investment opportunities (Bond et al., 2003). The baseline model is shown as following Eq. (3.1):

$$Log\ (Pat_{i,t}+1) = \beta_1 Log\ (Pat_{i,t-1}+1) + \beta_2 Log\ (Pat_{i,t-1}+1)^2 + \beta_3 S_{i,t-1} + \beta_4 Cf_{i,t-1} + \beta_5 Dbt_{i,t-1} + \beta_6 Sub_{i,t-1} + V_i + V_t + V_o + V_j + V_p + e_{i,j,o,p,t} \qquad (3.1)$$

$Pat_{i,t}$ is the measure of firms' innovation output calculated by the number of patent applications for a firm *i* in a given year *t*. However, we encounter a problem that in our dataset the majority of observations have zero patent filings (that is $Pat_{i,t}$ equals 0) because the majority of firms do not submit patent applications to the SIPO during the sample period. Thus, we construct a measure of $Pat_{i,t}$ by using the natural logarithm of it - $Log\ (Pat_{i,t}+1)$ to avoid the problem of too many zeros. We then employ the transformation $Log\ (Pat_{i,t}+1)$ as the dependent variable in our regression models. We choose the application year of one patent rather than the grant year because the patent's application year can better capture the actual time of innovation (Griliches et al., 1986).

Using patents to measure innovation output has pros compared to other proxies (Bronzini & Piselli, 2016). Specifically, first, patents are less exposed to personal or subjective considerations. Second, patents are better to reflect innovation quality, because experts who can judge novelty and utility must examine one innovation product and then decide whether it can be patented. Third, Griliches (1990) suggests that patent activity can be interpreted as an indicator of the growth of economically valuable knowledge, and therefore a good measure of invention activity. Thus, given these advantages of patents, we believe that the number of patent applications is a suitable measure of innovation output in our empirical research.

In addition to patent filing data, there are other measures of innovation activities such as new product output value and R&D expenditure. Since in the NBS firm-level dataset the record of new product output value is incomplete,[94] we employ the variable of new product output value as an alternative measure of firms' innovation output to alleviate the potential measurement error of innovation output to enhance robustness. We also choose the variable of R&D expenditure as a measure of firms' innovation input for a robustness test to check whether the effect of subsidies on innovation keeps consistent.[95]

Our main explanatory variable is $Sub_{i,t}$ which represents total subsidies a firm i receives from governments in year t. We standardize the variable by using the variable itself divided by total assets. For other control variables, we denote a firm i's ratio of sales to total

[94] The data of new product output value is available from the years 1998-2008 but missing in 2004 and 2008. Thus, during the sample period 1998-2008 in the study, the new product output value is less satisfactory than patent filing.

[95] The data of R&D expenditure is only available for the years 2001-2003 and 2005-2007.

assets in year *t* as $S_{i,t}$, its ratio of cash flows to total assets in year *t* as $Cf_{i,t}$ and its ratio of new long-term debts to total assets in year *t* as $Dbt_{i,t}$.[96] All independent firm-level continuous variables are lagged by one year $(t-1)$ to meet the modified Euler equation to eliminate simultaneity issues. We also add some dummy variables into the regression model. V_i is firm fixed effects. V_t is year fixed effects to control the impact of economic cycle changes. V_o is ownership dummy variables to control the effects of different ownerships which are grouped based on the fraction of firms' registered paid-in capitals.[97] V_j is industry dummy variables because government subsidies are generally distributed to firms in emerging strategic industries or industries that governments need to support.[98] V_p is geographical dummy variables because the regional gap of economic development makes that firms in China's various places differ in their ability and probability to obtain subsidies from governments.[99] $e_{i,j,o,p,t}$ is an idiosyncratic error term. Table 3.1 shows the definitions of all regression variables in Eq. (3.1).

[*Insert Table 3.1 here*]

Table 3.2 shows the pairwise correlation analysis of the main regression variables. We find that except for the lagged innovation variable of $Log\ (Pat_{i,t-1}+1)$ and the lagged squared innovation variable of $Log\ (Pat_{i,t-1}+1)^2$, there is no collinearity between other variables. The correlation index between our dependent variable (innovation output variable of

---

[96] New long-term debts are the difference between the contemporaneous long-term debts and the lagged long-term debts. Thus, in the dataset observations with new long-term debts are recorded from 1999.

[97] Following Guariglia and Liu (2014), we choose the fraction of firms' registered paid-in capitals to construct firms' ownership categories. Based on the majority (at least 50%) of registered paid-in capital (see Ayyagari et al., 2010, for a similar approach), all firms are divided into six categories: state-owned enterprises (SOEs); foreign firms; private firms; collective firms; Hong Kong, Macao or Taiwan (HMT) firms; and mixed ownership firms. The detailed description of ownership classification is in Appendix D.

[98] Due to the limitation of statistical software packages, GB/T two-digit sector codes rather than three-digit codes and four-digit sector codes are used as industry dummies in Eq. (3.1) to control industry fixed effects.

[99] Here we use province codes as geographical dummy variables.

$Log\ (Pat_{i,t} + 1)$) and main explanatory variable (subsidy variable of $Sub_{i,t-1}$) is 0.0188 and the significance level is 1%, which can indirectly suggest a positive relationship between firms' patenting activities and government subsidies. The finding possibly shows that government subsidies have a promoting effect on firms' innovation output.

[*Insert Table 3.2 here*]

3.6. Summary statistics and empirical results

3.6.1. Summary statistics

Table 3.3 summarizes the means (and medians in parentheses) of the main variables for the full sample, firms with/without patent applications, SOEs and private firms. [100] The observations with patent applications (52,147) are approximately one out of twenty observations without patent applications (1,058,235), reflecting a low participation rate of patenting activities in China. Additionally, there are 90,124 SOE firm-year observations compared to 446,572 private firm-year observations (around 40% of the full sample), suggesting that private firms are still the main components of Chinese corporations.

[*Insert Table 3.3 here*]

It is no strange that firms with patent applications have a higher average value of $Log\ (Pat_{i,t} + 1)$ (1.454) than firms without patent applications, whose corresponding value is zero. We also find that innovative firms have a higher ratio of lagged government subsidies to

[100] We summarize the number of observations estimated into regressions. This is the reason that the number of total observations is 1,110,382. If we summarize the number of all observations in the panel (2,373,488), the findings remain qualitatively unchanged.

total assets (mean value of 0.260%) compared to that of non-innovate firms (mean value of 0.182%). The finding may indirectly reflect a positive relationship between firms' innovation activities and government subsidies. More subsidies received from the government possibly can increase firms' innovation activities. Moreover, innovative firms have a lower ratio of sales to total assets (mean value of 125.652%) compared to non-innovate firms (mean value of 192.177%). We also find that firms with patent applications have a lower ratio of cash flow to total assets (mean value of 8.645%) and a higher ratio of new long-term debt issue to total assets (mean value of 0.319%) compared to firms without patent applications (corresponding values are 9.752% and 0.064%). The finding may be caused by greater demand for external funds of R&D characteristics, which is that firms' limited internal finance generally cannot solo support their innovation activities. Therefore, innovative firms have to rely more on external finance. For other firm-level variables, patenting firms are larger and more mature in terms of real total assets (mean value of 776.732 million yuan) and age (mean value of 14.647 years old) compared to their non-patenting counterparts (corresponding values are 82.779 million yuan and 11.501 years old). Firms with patent applications are more politically affiliated (mean value of 66.575) and have more percentage of state shares (mean value of 10.231%) than firms without patent applications (corresponding values are 74.352 and 8.105%).[101] We also find innovative firms are more likely to locate in coastal regions (mean value of 1.320) rather than non-innovate firms (mean value of 1.357).[102]

Table 3.3 also compares SOEs and private firms. We find that SOEs own more innovation activities versus private firms, which can be shown by that the average values of all

[101] We define all variables in Appendix D to show that political affiliation is a categorical variable. In the Chinese dataset, its Chinese appellation is 'zhengzhilishu' (lishu). If the value of variable 'zhengzhilishu' one firm is higher, the firm tends to own less political affiliation. On the contrary, firms displaying lower values of variable 'zhengzhilishu' are more likely to be highly political affiliated or controlled by the government.

[102] We define coastal regions as 1, central regions as 2 and western regions as 3.

the three innovation indexes are higher for SOEs (average values of 0.083, 2.527% and 0.113% respectively) than private firms (average values of 0.054, 2.105% and 0.095% respectively). It is no doubt that the ratio of government subsidies to total assets for SOEs (mean value of 0.277%) is higher than private firms (mean value of 0.168%) since SOEs can easily obtain more subsidies from governments by using their close connection with governments.

3.6.2. Estimation method

One significant feature of our data is that the majority of firms do not own patent applications in some of the year, so our dependent variable $Log\ (Pat_{i,t} + 1)$ is left-censored at zero. Additionally, our data is a huge unbalanced panel. Considering firms' heterogeneity, we, therefore, employ the Random-effects Tobit estimator in this study (Tobin, 1958). To ensure robustness, we also estimate the Pooled Tobit based on the full sample. Since the Tobit is a non-linear estimation method, we estimate average marginal effects. According to Cong (2001), in the study, we report all three types of marginal effects of the Tobit estimation, which are the marginal effects on the probability, the quantity of truncated data, and the quantity of censored data.[103]

3.6.3. Empirical results

Table 3.4 shows the estimation results based on the full sample. We observe that more firms' subsidies received from governments increase both the likelihood and the intensity of firms' innovation activities. We report the estimation results of baseline Eq. (3.1) using

[103] According to Cong (2001), for the marginal effects in the probability, it measures how the probability of being uncensored changes with respect to the regressors; for the quantity of truncated data, it describes the changes in dependent variable with respect to changes in the regressors among the subpopulation for which dependent variable is not at a boundary. For the quantity of censored data, it measures how the observed dependent variable changes with respect to the regressors.

Random-effects estimation in Table 3.4. In columns (1) to (3), we find that the marginal effects of the subsidy variable ($Sub_{i,t-1}$) are all significant and negative. To be specific, the magnitude of the marginal effect in the probability of $Sub_{i,t-1}$ in column (1) is 0.193 (19.3%) and significant at the 1% level, which means that a 10% increase in the ratio of firms' subsidies received to total assets is associated with an average increase of 0.0193 (1.93%) in the probability that firms own patent applications. The magnitude of the marginal effect in the quantity of truncated data of $Sub_{i,t-1}$ in column (2) is 0.721 (72.1 %) and significant at the 1% level, suggesting as the ratio of firms' subsidies received to total assets increases by 10%, the number of patent applications rises by 0.0721 (7.21 %) for firms with patent applications. The marginal effect in the quantity of censored data of $Sub_{i,t-1}$ in column (3) is 0.238 (23.8%) and significant at the 1% level, showing that a 10% increase in the ratio of firms' subsidies received to total assets leads to an average increase of 0.0238 (2.38%) in the number of patent applications for firms with/without patent applications. The estimation results clearly show that there is a positive and significant relationship between firms' subsidies obtained from governments and firms' innovation activities. The results suggest that more government subsidies could promote more firms' innovation activities, verifying the supplement effect of subsidies to innovation funds since government subsidies could increase firms' motivation for innovation and reduce information asymmetry between firms and market investors.

[*Insert Table 3.4 here*]

For other control variables, we find that that the marginal effects of $Log\ (Pat_{i,t-1} + 1)$ on $Log\ (Pat_{i,t} + 1)$ are all positive and significant at the 1% level and the marginal effects associated with $Log\ (Pat_{i,t-1} + 1)^2$ are all negative and significant at the 1% level, keeping consistent with the theoretical assumption. The signs of the marginal effects of $S_{i,t-1}$ are all significantly negative at the 1% level. The finding could be explained by the short-sighted behaviours of Chinese firms, suggested by that Chinese firms would not innovate as their market shares expand. Although the marginal effects of $Cf_{i,t-1}$ and $Dbt_{i,t-1}$ are all significantly positive at the 1% level, we find that the magnitudes of the marginal effects of $Cf_{i,t-1}$ are all larger than those of $Dbt_{i,t-1}$, showing that firms prefer internal finance (cash flow) to external finance (bank loans) to support patent activities. We also estimate the Pooled Tobit in columns (4) to (6) and find the empirical results keep qualitatively unchanged.

3.7. Endogeneity issues and robustness tests

A major challenge in our main regressions is that government subsidies are likely endogenous. Firms with more innovation activities are more likely to obtain subsidies from governments (more innovation, more subsidies), that is, a reverse causality between corporation innovation and government subsidies. In Section 3.7.1 and Section 3.7.2, we implement the instrumental variable (IV) approach and the quasi-natural experiment to confirm the causal effect of subsidies on innovation. To further circumvent endogeneity issues associated with potential omitted variables and measurement errors, in Section 3.7.3, we add the contemporaneous terms of the firm-level financial variables at the right-hand side to control for potential omitted variables. In Section 3.7.4, we use alternative measures of firms' innovation activities to alleviate potential measurement errors in our regression model.

3.7.1. Instrumental variable (IV) approach

In this section, we employ the instrumental variable (IV) method. The first IV used for government subsidies received by firms ($Sub_{i,t}$) is the amount of annual public finance revenue in prefecture-level cities divided by the number of firms in prefecture-level cities each year

($Fin\_Rev_{c,t}$).[104] Since government subsidies come from public finance revenue, the more public finance revenue in a city, the more subsidies from governments for firms in the city. We also employ the median value of government subsidies in each year-city level ($Med\_Sub_{c,t}$) as the second IV since it is likely to be closely linked to firms' government subsidies. Both two instrument satisfies the relevance condition of the instrument but is unlikely to be affected by firms' decisions on innovation.

Table 3.5 reports the estimation results of the IV method. Columns (1) to (4) show the results when $Sub_{i,t-1}$ is only instrumented by $Fin\_Rev_{c,t-1}$. Column (1) shows the first-stage regression results based on Newey's two-step estimator (Newey, 1987).[105] The coefficient value of $Fin\_Rev_{c,t-1}$ (0.003%) shows that the ratio of public finance revenue divided by the number of firms at the prefecture-city level ($Fin\_Rev_{c,t-1}$) is significantly and positively correlated with the subsidies received by firms from governments. The findings suggest that firms tend to obtain more government subsidies when they are located in cities where local governments have more public finance revenues. The statistical first-stage F-value (418.100) is far greater than the rule of thumb of 10, showing that the IV ($Fin\_Rev_{c,t-1}$) is valid and does not suffer from a possible weak instrument bias (Staiger & Stock, 1997; Stock & Yogo, 2005). Columns (2) to (4) demonstrates the second-stage estimation results when $Sub_{i,t-1}$ is only instrumented by $Fin\_Rev_{c,t-1}$. Although the magnitudes of the marginal effects of $Sub_{i,t-1}$ (41.993%, 153.064%, and 58.750% respectively) are larger compared to those of our main

---

[104] Information on public finance revenue at the city level is collected from the *China City Statistical Yearbook*.

[105] For the IV Tobit estimation in STATA process, we have to add the option 'twostep' after the code 'ivtobit' to estimate the first-stage regression results, which is based on Newey's two-step estimator. For the marginal effects of the second-step regression results, we could employ the default estimator of maximum likelihood instead of the option 'twostep'.

empirical results, we find that all marginal effects of the instrumented $Sub_{i,t-1}$ remain statistically significant and positive.

[*Insert Table 3.5 here*]

Columns (5) to (8) show the estimation results when $Sub_{i,t-1}$ is instrumented by $Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$. Column (5) shows the first-stage regression results, and it is no doubt that the median value of government subsidies in each year-city level ($Med\_Sub_{c,t-1}$) is significantly and positively (198.118%) correlated with government subsidies received by firms. The coefficient of $Fin\_Rev_{c,t-1}$ remains statistically significant and positive (0.003%). The first-stage estimation results confirm the relevance of these two IVs to subsidy variable ($Sub_{i,t-1}$). The statistical first-stage F-values (418.190) is larger than the rule of thumb of 10, suggesting that the instrumental variables ($Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$) are valid and do not face a potential weak instrument bias. Columns (6) to (8) report the second-stage estimation results when $Sub_{i,t-1}$ is instrumented by $Fin\_Rev_{c,t-1}$ and $Med\_Sub_{c,t-1}$. We find that the marginal effects of $Sub_{i,t-1}$ are all positive (7.591%, 27.674%, and 10.619% respectively) at the 1% significant level, which keeps consistent with our main empirical results. The estimation results of the two IV methods verify that government subsidies have a positive effect on firms' innovation activities in China, even after considering the endogenous nature of subsidies.

To evaluate the validity of the instruments, we conduct a Wald test of exogeneity and an Anderson-Rubin (AR) test. Specifically, the Wald test measures whether the error terms in the structural equation and the reduced-form equation for the endogenous variables are correlated. In Table 3.5, the significant p-value statistics (0.000) suggest that our regressors are not exogenous and confirm the necessity of introducing instrumental variables. The AR test is a joint test of the structural parameter and the exogeneity of the instruments. The null hypothesis of the AR test is that all regressors are exogenous and the minimum canonical correlation is zero. In Table 3.5, the significant p-value statistics (0.000) lower than 0.05 suggest that our model is identified and/or our instruments are valid. Additionally, we also conduct a Hausman test and a Smith-Blundell test to confirm the existence of endogenous variables (Smith & Blundell, 1986).

3.7.2. Quasi-natural experiment

In this section, we provide clear identification of the causal effect of subsidies on innovation by using a difference-in-differences (DID) specification. In 2006, the State Council of China initiated the 'National Program for Medium- and Long-term Scientific and Technological Development' to promote innovation. As a response to the central strategy, some local authorities changed their subsidy policies for patent applications. For example, in 2006, Zhangjiagang, one county-level city of Suzhou (a prefecture-level city in Jiangsu province) revised its subsidy policies for patent applications by increasing the number of subsidies per the patent application, while subsidy policies in other neighbouring county-level cities of Suzhou remained unchanged (Lei et al., 2012). Specifically, before 2006, the county-level cities of Suzhou have the same subsidy policies for the patent application, which is implemented in 2003.[106] On June 12th, 2006, Zhangjiagang increases the number of subsidies from 1,500 yuan, 1,000 yuan and 500 yuan to 3,000 yuan, 1,500 yuan and 1,000 yuan for applications of invention patents, utility model patents, and design patents, respectively. It also awards more than 10,000 yuan for the grant of each invention patent application. However, at the same time, the subsidy policies in other county-level cities of Suzhou remain unchanged.[107]

---

[106] In 2006, Suzhou prefecture-level city is made up of 7 county-level districts (Municipal districts, Canglang, Pingjiang, Jinchang, Huqiu, Wuzhong, and Xiangcheng) and 5 county-level cities (Changshu, Zhangjiagang, Kunshan, Wujiang, and Taicang). The county-level districts are the centre areas of one prefecture-level city. Thus, we make a combination of all seven county-level districts and call it as Suzhou urban districts.

[107] The detailed information of the amount of subsidies of patent applications for all county-level cities of Suzhou are shown in Appendix F.

Thus, the exogenous shock to subsidies for firms' patent applications in Zhangjiagang provides us with an ideal opportunity of using a quasi-natural experiment to identify the causal effect of subsidies on patent filings.

For the specification, first, we choose a dummy variable $Treat$ that equals 1 for the treatment group (firms distributed in Zhangjiagang) and 0 for the control group (firms distributed in other neighbouring county-level cities of Suzhou), which can capture the difference in $Log(Pat_{i,t} + 1)$ between the treatment and control groups before the policy revision. Second, to separate the full sample period into the pre-revision and post-revision periods, we employ a time dummy variable $Post$ that equals 1 starting from 2006 and 0 otherwise, which can check the difference in $Log(Pat_{i,t} + 1)$ between the pre-revision and post-revision periods for the firms in the control group. The aggregate factors that could change $Log(Pat_{i,t} + 1)$ can be captured by the dummy variable $Post$, even in the absence of the policy revision in 2006. Third, we construct an interaction term ($Treat * Post$) to yield the average treatment effect, which compares the difference between the treatment and control groups in their average differences between the pre-revision and post-revision periods. Last, we replace the subsidy variable ($Sub_{i,t-1}$) with the interaction term ($Treat * Post$) in baseline Eq. (3.1) to re-estimate.[108]

Table 3.6 shows the estimation results of marginal effects in the quantity of censored data based on our DID specification due to space limitation, while the other two types of marginal effects keep qualitatively unchanged. In column (1) when we do not include other control variables, the marginal effect of the interaction term ($Treat * Post$) is statistically significant and positive (0.047), suggesting that after the revision of subsidy policies in 2006,

---

[108] We employ county-level cities as the geographical dummy variables since we estimate the subsample of firms in Suzhou.

firms in Zhangjiagang with better patent subsides undertake more patenting activities than firms in other county-level cities. The marginal effect of the single term ($Treat$) is significant and positive, suggesting that the firms in Zhangjiagang have more a greater number in $Log(Pat_{i,t}+1)$ than firms in other county-level cities in the pre-treatment period. The significant positive marginal effect of the single term ($Post$) shows a positive trend in $Log(Pat_{i,t}+1)$ for the firms in other county-level cities from the pre-revision to post-revision periods. However, we only need to observe the marginal effect of the interaction term ($Treat * Post$). The main effect of the single term ($Treat$) only applies when $Post$ equals 0, which can capture the difference in $Log(Pat_{i,t}+1)$ in the pre-treatment period. The main effect of the single term ($Post$) also applies when $Treat$ equals 0. In column (2) when we include other control variables, we find the marginal effect of the interaction term keeps statistically significant and positive (0.080).[109] We do not include county dummy variables and year dummy variables because doing it would introduce collinearity with the single terms of $Treat$ and $Post$. In column (3) we check when we add the geographical effect (V_p) and the year effect (V_t) in estimation but do not cover the single terms of $Treat$ and $Post$, and the estimated marginal effect of the interaction term ($Treat * Post$) keeps qualitatively unchanged (0.079).[110] The findings confirm our main empirical results and then successfully test the causal effect of subsidies on innovation.

[*Insert Table 3.6 here*]

Next, we conduct a series of validity checks for the experiment setting and report the estimation results in Table 3.6. In column (4), we make a test for the ‘parallel trend’ assumption,

[109] Due to space limitation, we do not show the estimation results of other control variables while they keep qualitatively consistent with our main empirical results.

[110] Here we use the codes of county-level cities to reflect the geographical effect.

which is necessary for a DID approach. Specifically, we use a flexible estimation by constructing a time series of interaction terms between $Treat$ and the year dummies for the full sample period, that is, $Treat * Year$ with $Year$ indicating 2000 through 2008.[111] The estimation also could remedy the drawback that the interaction term ($Treat * Post$) does not consider year-to-year changes. The estimated marginal effects of these interaction terms are all statistically insignificant for years before 2006, showing that before the policy revision in 2006 there is no significant change for the difference in firms' patenting activities between the treatment and control groups. Thus, the 'parallel trend' assumption of patenting activities for the two groups before the revision could be achieved. Meanwhile, the marginal effects of the interaction terms become statistically significant and positive for every year from 2006 outwards. Specifically, the magnitude of the marginal effect of $Treat * Year2007$ (0.111) is higher than that of $Treat * Year2006$ (0.055) and $Treat * Year2008$ (0.059), showing that the revision has the largest promoting effect on innovation in the year 2007. The results again verify the dynamics of the impact of the revision on innovation.

We also plot the differences in average response outcomes between the treatment and control groups from the pre- to post-revision periods in Fig. 3.7 and Fig. 3.8. First, we find that both groups show a similar trend in outcomes before the revision in 2006 so the differences of patent applications are small. Specifically, for Fig. 3.7 the difference in the patent participation rate is approximately between -1% and 1% before 2006 and for Fig. 3.8 the difference in the number of patent applications is negative before 2006. Second, both groups show different trends in outcomes after the revision in 2006 so the differences in patent applications become large. Specifically, for Fig. 3.7 the difference in the patent participation rate reaches more than

[111] We introduce in the Note 27 that the data in years 1998 and 1999 are used to construct control variables. Thus, the estimation for the full sample covers years from 2000 to 2008. The benchmark is the interaction term $Treat * Year2000$ for the next interaction terms $Treat * Year$ from 2001 to 2008.

2% after 2006 and for Fig. 3.8 the difference in the number of patent applications substantially increases to approximately 100 after the year 2006. The figures show that our DID method satisfies the parallel trend assumption.

[*Insert Fig. 3.7 here*]

[*Insert Fig. 3.8 here*]

We take more placebo tests for the validity check and report them in Table 3.6. First, we assume that the policy revision happened in 2005 and construct the dummy variable $Post$ equals 1 starting from 2005 and 0 otherwise. The dummy variable $Treat$ keeps unchanged, 1 for firms in Zhangjiagang and 0 for firms in other county-level cities. We then run the data until the year 2006 before the policy revision and the marginal effect of the interaction term ($Treat * Post$) reported in column (5) is statistically insignificant, suggesting that if the policy revision happened in 2005, firms' patenting activities of firms in Zhangjiagang could not be affected. Second, we assume that one of the other county-level cities without the policy revision such as Changshu (one of the county-level cities of Suzhou) is affected by the policy revision, and thus construct the dummy variable $Treat$ equals 1 for firms in Changshu and 0 otherwise. The dummy variable $Post$ keeps unchanged, 1 starting from 2006 and 0 otherwise. In column (6) we report the marginal effect of the interaction term ($Treat * Post$) that is statistically insignificant, suggesting that firms' patenting activities in Changshu are not affected by the policy revision. The estimation results of the placebo tests suggest an only revision of subsidy policy in Zhangjiagang in 2006 has a causal impact on innovation.

3.7.3. Potential omitted variables- adding the contemporaneous terms

As mentioned above, the baseline Eq. (3.1) only considers the impact of lagged terms of independent variables while contemporaneous terms may also affect firms' innovation activities. Thus, an estimation bias of omitted variables would appear. To address the concern, we include the contemporaneous terms of all firm-level financial variables to augment the baseline Eq. (3.1). Specifically, we not only add the contemporaneous subsidy variable ($Sub_{i,t}$) but also include the contemporaneous cash flow variable ($Cf_{i,t}$) as firms' R&D projects are largely affected by their contemporaneous internal cash flow. Also, since there is a potential correlation between internal cash flow and sales (Dechow et al., 1998), we add the contemporaneous sales variable ($S_{i,t}$) in the regression to avoid an estimation bias. We also add the contemporaneous term of the new long-term debt issue ($Dbt_{i,t}$) into the specification.

Table 3.7 shows the estimation results of the augmented Eq. (3.1) covering contemporaneous terms of all firm-level financial variables. We find that the estimation results keep qualitatively consistent with those of our main results: the sum of the marginal effects of subsidy variables ($Sub_{i,t-1}$ and $Sub_{i,t}$) is still statistically significant and positive. Specifically, in columns (1) to (3), the magnitudes of the sum of the marginal effects of subsidy variables ($Sub_{i,t-1}$ and $Sub_{i,t}$) are 0.275, 1.015 and 0.331 respectively and significant at the 1% level, verifying that more subsidies increase innovation activities. Besides, we notice that the magnitudes of the contemporaneous subsidy variable are larger (0.191, 0.704, and 0.229, respectively) compared to those of the lagged subsidy variable (0.084, 0.311 and 0.101 respectively), showing that contemporaneous subsidies have a larger positive effect on innovation activities. The findings confirm the necessity of including the contemporaneous terms in the estimation.

[*Insert Table 3.7 here*]

3.7.4. Potential measurement errors - alternative measures of innovation

In our main results, we use the number of patent applications per firm to measure innovation output. However, using the number of patent applications to measure innovation output still has disadvantages in a brief discussion as not all innovation outputs would be patented (Griliches, 1990). Specifically, first, the requirements of patent applications are strict. The number of patent applications cannot fully reflect the further improvement for products that have been patented, thus firms' innovation performance may be undervalued. Second, to secure business economic returns, firms might not patent their innovation outputs to avoid the premature leakage of innovation information. Only innovation outputs whose patents have economic value above a certain minimal threshold are patented (Griliches, 1990). Third, China's relatively weak IRP also can hamper firms' enthusiasm for patent applications. Thus, using the number of patent applications may yield measurement bias for innovation output. For mitigating this issue, we further measure firms' innovation output by using the ratio of firms' new product output value to total assets ($Np_{i,t}$) in baseline Eq.(3.1) to re-estimate.[112] Compared to the number of patent applications, new product output value can reflect the industrialization performance of innovation achievements. In other words, new product output value can measure commercialized innovation output while patents can only measure technological innovation outputs (Guo et al., 2016). Besides that, we also choose the ratio of firms' R&D

[112] In the *China Statistical Yearbook* (2006), new products are defined as "those new to the Chinese market that either adopt completely new significant principles, technologies or designs, or are substantially improved in comparison with existing products in terms of performance and functionality, through significant changes in structure, materials, design or manufacturing process." As a good indicator of innovation output, new product output value has been widely used in recent papers related to innovation (Henard & Szymanski, 2001; Guariglia & Liu, 2014). Because in the NBS firm-level dataset the variable of new product output values is only recorded from 1998 to 2007 and missing in 2004, we have to make it as a robustness test.

expenditure to total assets ($Rd_{i,t}$) to proxy firms' innovation activities based on R&D input level to estimate baseline Eq. (3.1).

Table 3.8 shows the corresponding estimation results. In columns (1) to (3) when firms' innovation output is measured by the ratio of firms' new product output value to total assets, we find that the signs of the marginal effects of $Sub_{i,t-1}$ still keep significantly positive (0.083, 0.047, and 0.024). Next, in columns (4) to (6), the marginal effects of $Sub_{i,t-1}$ are also statistically significant and positive (0.406, 0.006, and 0.004) when innovation activities are measured by the ratio of firms' R&D expenditure to total assets. The findings of the robustness tests suggest that no matter which proxy of innovation activities we employ, the positive effect of subsidies on innovation can hold.

[*Insert Table 3.8 here*]

3.7.5. Additional robustness tests

Besides the aforementioned estimation methods, our results keep consistent when we employ various robustness tests. First, following some studies (Lei et al., 2012; Li, 2012), since invention patents represent good-quality patents, we only select the number of invention patent applications to proxy firms' innovation output. Compared to two other types of patents, invention patents are the most technologically innovative and require more R&D efforts. Second, since the number of patent applications per firm is a count variable, the majority of whose values are 0, we employ the Zero-inflated Poisson method to estimate again.[113] Third,

[113] In our main estimations, we do not winsorize the innovation output variable of $Log\ (Pat_{i,t}+1)$ since we employ the natural logarithm to eliminate the effect of discrete values. In the part, we winsorize the number of patent applications per firm that is not presented by the natural logarithm ($Pat_{i,t}$) at its 99 percentage to avoid the influence of extreme values. Additionally, according to Vuong (1989), since the statistics value of Vuong in our estimation is relatively large (67.37>1.96), we should choose Zero-inflated Poisson regression rather than standard Poisson regression.

since we choose the natural logarithm of the number of patent applications as the dependent variable, we also use the natural logarithm to standardize firm-level financial variables to estimate. Fourth, due to the data limitation in the year 2008, we choose an alternative sample excluding the data in the year 2008 to estimate. Table 3.9 shows the results of all robustness estimations that remain qualitatively unchanged with our main empirical results.[114]

[*Insert Table 3.9 here*]

3.8. Further tests

3.8.1. Firms' ownership

There are significant differences between firms of various ownerships in resource acquisition and signal transmission through the mechanism of using subsidies for innovation (Liang et al., 2012). In Table 3.10, we test whether there is a difference in the effect of subsidies on innovation between the two groups of firms.

[*Insert Table 3.10 here*]

Using a Random-effects Tobit estimator, our results show that the marginal effects of $Sub_{i,t-1}$on $Log\ (Pat_{i,t}+1)$ for SOEs are all significantly greater than those of private firms. Specifically, for private firms in columns (2), (4) and (6) the marginal effect in the probability of $Sub_{i,t-1}$ is 0.294, the marginal effect in the quantity of $Sub_{i,t-1}$ of truncated data is 1.237, and the marginal effect in the quantity of $Sub_{i,t-1}$ of censored data is 0.375. The marginal effects are all significant at the 1% level. By contrast, in columns (1), (3) and (5) the marginal

[114] For brevity, we only report the marginal effects in quantity of censored data.

effects of $Sub_{i,t-1}$ for SOEs are statistically insignificant. The p-values associated with the t-tests for the equality of the marginal effects between SOEs and private firms show that these differences are significant. The results suggest that government subsidies have a more promoting effect on patenting activities of private firms rather than those of SOEs.

The difference in the effect of subsidies on innovation between SOEs and private firms could be explained as follows. First, from the perspective of resource acquisition, compared to private firms, SOEs could easily get financial support from governments such as subsidies because SOEs are controlled or operated by governments (Li et al., 2008; Guariglia & Mateut, 2016). The financial advantage could cause a problem of soft budget constraints to SOEs (Lin & Tan, 1999; Chow et al., 2010; Liang et al., 2012), which makes that using subsidies to promote innovation performance is not important for SOEs. Additionally, the financial advantage of SOEs could result in a problem of resource slack that deepens the agency problem (Greve, 2003). Thus, the incentives of using subsidies to innovate are not strong for managers of SOEs. They are likely to invest in less risky activities rather than R&D. Second, administratively appointed managers of SOEs often lack professional management ability, which also weakens the efficiency of SOEs in transforming innovative resources such as subsidies into innovative output (Cuervo & Villalonga, 2000; Carman & Dominguez, 2001). By contrast, although private firms have a high enthusiasm for innovation, they are normally constrained by available funds due to the 'lending bias' in China (Chen et al., 2012).[115] Thus, using subsidies to promote innovation performance is important for private firms. Third, private firms have more autonomy and flexibility in the implementation of innovation strategy

[115] Due to the unique state-dominated financial system in China, compared to SOEs, private firms face institutional discrimination from state-controlled 'Big-five' commercial banks that have always been dominant players in China's financial markets. The 'Big-Five' commercial banks in China are Bank of China Limited, Agricultural Bank of China Limited, Industrial and Commercial Bank of China Limited, China Construction Bank Corporation, and Bank of Communications.

compared to SOEs, since private firms do not face the problems that SOEs have such as managers' administration promotion pressure, redundant employees, policy burdens (Lin & Tan, 1999). These organizational advantages enable private firms to transform innovative resources into innovative output more effectively (Liang et al., 2012).

3.8.2. Heterogeneity on firms' financing constraints

Since the 'lending bias' existed in China's financial market, firms in China generally have a disparity in financial constraints. Thus, we further take the heterogeneity of firms' financial constraints into account. Specifically, we first use firms' size and age to measure firms' financial constraints due to two reasons. First, small and young firms generally face high-cost external financing since they are typically characterized by high idiosyncratic risk and high bankruptcy costs (Carpenter et al., 1994; Chirinko & Schaller, 1995; Czarnitzki & Hottenrott, 2011; Guariglia & Yang, 2016). Second, small and young firms cannot enjoy the benefits of economies of scale that large and mature firms own, thus they do not have enough physical assets as collateral or long records of accomplishment to obtain external finance such as bank loans. Thus, compared to large and mature firms, small and young firms have a large probability of facing more financial constraints. Second, we choose firms' political affiliation and state shares as proxies of firms' financial constraints. Since firms with political affiliation and firms with state shares are more likely to obtain loans from the bank system dominated by state capitals (Johnson & Mitton, 2003; Khwaja & Mian, 2005) and thus face less financial constraints compared to firms without political affiliation and firms without state shares. Last, Following Hadlock and Pierce (2010), we also construct the SA index to measure firms' financial constraints. Firms with a higher SA index are more financially constrained firms, while firms with a lower SA index are less financially constrained firms.

Table 3.11 shows the estimation results based on firms' heterogeneity on financial constraints. Due to space limitation, we only report marginal effects in the quantity of censored data while the estimation results of the other two types of marginal effects keep qualitatively consistent. In columns (1) and (2) showing the estimation results of small firms and large firms, we find that the marginal effect of $Sub_{i,t-1}$ on $log\ (Pat_{i,t}+1)$ is significantly stronger for small firms (0.212) rather than large firms (0.152). In columns (3) and (4), we observe that the marginal effect of $Sub_{i,t-1}$ for young firms (0.305) is significantly higher than that for mature firms (0.203). The results suggest that the positive effect of government subsidies on patenting output is more pronounced for small firms and young firms rather than their large counterparts and mature competitors.

[*Insert Table 3.11 here*]

Table 3.11 also compares firms without political affiliation and firms with political affiliation in columns (5) and (6), firms without state shares and firms with state shares in columns (7) and (8). We find that the marginal effect of $Sub_{i,t-1}$ on $log\ (Pat_{i,t}+1)$ for firms without political affiliation (0.460) is statistically significant at the 1% level, while insignificant 0.044 for firms with political affiliation. Besides, the positive marginal effect of $Sub_{i,t-1}$ for firms without state shares is larger (0.256) and more significant (at the 1% level) than that for firms with state shares (its magnitude is 0.145 at the 10% significant level). The results show that patenting activities of firms without political affiliation and firms without state shares are more positively affected by government subsidies than those of firms with political affiliation and firms with state shares.

Based on firms' size and age, we also construct the index of firms' financial constraints – the SA index and divide the full sample into two parts: firms with low SA index and firms with high SA index. The former are less financially constrained firms while the latter are more financially constrained firms. Table 3.11 displays the estimation results of firms with a low level of SA index and firms with a high level of SA index. Specifically, in columns (9) and (10). we find that the marginal effect of $Sub_{i,t-1}$ is significantly 0.204 for firms with a high SA index while only significantly 0.173 for firms with a low SA index. The findings show that government subsidies have a stronger effect on innovation activities of firms with a high SA index than those of firms with a low SA index.

In short, the positive effect of subsidies on innovation is more pronounced for more financially constrained firms, suggesting that the supplement effect of subsidies on innovation is stronger for firms with more financial constraints. Specifically, the supplement effect is stronger for small firms, young firms, firms without political affiliation, firms without state shares, and firms with a high SA index rather than their counterparts: large firms, mature firms, firms with political affiliation, firms with state shares and firms with low SA index. The p-values associated with the t-tests for the equality of the marginal effects between high financially constrained firms and low constrained firms show that these differences are significant at the 1 % level.

3.8.3. Industry heterogeneity

Due to the different characteristics of industries and cities, we also test what changes to the positive effect of subsidies on innovation based on different industries and cities. For industries, we first compare firms in industries with different levels of external finance dependence (EFD) and second compare firms in industries with different levels of high-tech intensiveness. For EFD, we follow Rajan and Zingales (1998) and Acharya and Xu (2017) to compute the level of industry EFD. Specifically, we first calculate the fraction of firms' capital expenditure that cannot be financed by their internal cash flow to proxy firms' EFD. Then, we obtain the median value of all firms' EFD in one industry each year to construct a time series of the industry's EFD level. Finally, we choose the median value of the time series of one industry's EFD level as the industry's dependence on external finance ($Dependence_j$) over the period 1998 to 2008. As regards the classification of high-tech intensiveness, we make it based on the 'High-tech industries classification' conducted by the NBS of China.[116] The industries whose codes are listed in the classification are regarded as the industries with high-tech intensiveness and the rest as the industries without high-tech intensiveness. We construct a dummy variable ($High - tech_j$) that equals 1 for the industries with high-tech intensiveness and otherwise as 0. To test the changes to the positive effect of subsidies on innovation concerning industry variables, we construct the interaction terms ($Sub_{i,t-1} * Dependence_j$ and $Sub_{i,t-1} * High - tech_j$) and respectively add them into baseline Eq. (3.1) to re-estimate.

Table 3.12 shows the estimation results with industry variables. In columns (1) to (3), we find that the marginal effects of the interaction term ($Sub_{i,t-1} * Dependence_j$) show statistically significant and negative (-0.513, -1.888 and -0.615), indicating that the positive effect of subsidies on innovation would be reduced with higher industry EFD. The explanation is that a higher EFD in China may reflect a greater borrowing capacity for firms. Thus the supplement effect of subsidies on innovation funds would be alleviated for these firms with a strong financing ability. The magnitudes of the single term of $Sub_{i,t-1}$ become smaller (0.158, 0.583 and 0.190) compared to those in Table 3.4, which is not particularly interesting given that the main effect of $Sub_{i,t-1}$ only applies when $Dependence_j$ equals zero. The same also applies to the single term ($Dependence_j$).

[*Insert Table 3.12 here*]

[116] The website link of the classification of high-tech industries could be browsed via: http://www.stats.gov.cn/tjsj/tjbz/201812/t20181218_1640081.html.

Next, in columns (4) to (6), the marginal effects of the interaction term ($Sub_{i,t-1} * High-tech_{j,t-1}$) are statistically significant and positive (0.279, 1.034, and 0.384), which means that the positive effect of subsidies on innovation is stronger for firms in industries with high-tech intensiveness. The finding is possibly interpreted by that firms in industries with high-tech intensiveness generally have a greater demand for funds to support their large number of innovation activities caused by their industry characteristics, thus having a higher incentive of using subsidies to stimulate R&D. As a comparison, firms in industries without high-tech intensiveness do not have a high requirement of innovation funding.

3.8.4. City heterogeneity

For cities, we first compare firms in cities with different levels of financial development and second compare firms in cities with different levels of foreign direct investment. Following Hsu et al. (2014), we use the ratio of deposits to gross regional product (GRP), the ratio of loans to GRP, and the ratio of household savings to GRP to respectively measure city-level financial development in years ($Fin-dev_{c,t}$). For city-level foreign direct investment in years ($For-inv_{c,t}$), we employ the natural logarithm of the number of foreign new contracts signed, the ratio of agreed foreign investment to GRP, and the ratio of actual foreign investment to GRP to proxy it. Information on all city-level financial variables is collected from the *China City Statistical Yearbook*.[117] As similar to the industry variables, for exploring the influence of city-level financial variables on the positive effect of subsidies on innovation, we construct the related interaction terms ($Sub_{i,t-1} * Fin-dev_{c,t-1}$ and $Sub_{i,t-1} * For-inv_{c,t-1}$) and put them into baseline Eq. (3.1) to re-estimate, respectively.

[117] In the *China City Statistical Yearbook*, the data related to financial development is recorded from 2003 and the data related to foreign direct investment is recorded from 2000.

Table 3.13 presents the corresponding estimation results. In panel A, we find that the marginal effects of the interaction term ($Sub_{i,t-1} * Fin - dev_{c,t-1}$) are statistically significant and negative, regardless of which measures of the city-level financial development, showing that higher financial development would reduce the stimulating effect of subsidies on innovation. The finding could be explained by that firms located in cities with a higher level of financial development are more likely to easily obtain funds from the banking system since banks in these cities have a strong lending capacity. If financial development could mitigate the financing constraints faced by innovative firms. The promoting effect of subsidies on innovation may be reduced.

[*Insert Table 3.13 here*]

In Panel B of Table 3.13, we find that the marginal effects of the interaction term ($Sub_{i,t-1} * For - inv_{c,t-1}$) are statistically significant and negative, suggesting that higher city-level foreign direct investment would also decrease the positive effect of subsidies on innovation. The interpretation is similar to that of financial development. Since firms could enjoy the benefits of financing sources from foreign direct investment, the positive effect of subsidies on innovation would decrease.

3.8.5. Indirect effect of subsidies on innovation

In Section 3.6.2, we have tested the impact of subsidies on firms' innovation and we could define the impact as the direct effect of subsidies on innovation. However, subsidies may have an indirect effect of subsidies on innovation, especially for firms without subsidies. In this section, we further explore the indirect effect of subsidies on firms' innovation.

First, we define industry (j) groups and geographical (c) areas as industry-city clusters (j, c). The definition (rather than using clusters based solely on, say, industry classification, or regions) provides us with a sufficiently large number of clusters. Second, we construct a new subsidy variable to represent the proportion of firms with subsidies in one cluster, which is $Sub-Propor_{j,c,t} = N1_{j,c,t}/N2_{j,c,t} = \sum_i^{N2} d_{i,j,c,t}/N2_{j,c,t}$. We define $N1_{j,c,t}$ as the number of firms with subsidies in one cluster (j, c) and year (t) and $N2_{j,c,t}$ as the number of all firms in one cluster (j, c) and year (t). $d_{i,j,c,t}$ is a binary variable which equals 1 if one firm (i) receives subsidies in one cluster (j, c) and year (t) and equals 0 if not. Third, we add $Sub-Propor_{j,c,t-1}$ into Eq. (3.1) to test its effect on firms' innovation.

Table 3.14 shows the corresponding estimation results. We find the marginal effect in the probability of the interaction term ($Sub_{i,t-1} * Sub-Propor_{j,t-1}$) in column (1) is significant and negative, suggesting that the positive effect of subsidies on innovation is reduced as the proportion of firms with subsidies in one cluster increases. The marginal effect in the quantity of truncated data in column (4) and the marginal effect in the quantity of censored data in column (7) keep significant and negative. The finding could be explained that a high probability of obtaining subsidies reflected by an increasing number of firms with subsidies could decrease the initial positive effect of subsidies on firms' innovation. Since an increasing number of firms obtaining subsidies could reduce the number of subsidies distributed to each firm in the cluster, firms' innovation funds would be reduced and thus the promoting effect of subsidies on innovation decreases. Furthermore, we use $Sub-Propor_{j,t-1}$ instead of $Sub_{i,t-1}$ to explore the indirect effect of subsidies on innovation by dividing the full sample into two groups: firms with subsidies and firms without subsidies. The estimation results are reported in columns (2) and (3), and the marginal effect in the probability of $Sub-Propor_{j,t-1}$ on innovation is significant and positive for firms without subsidies while insignificant for firms with subsidies. The finding shows that subsidies have a greater positive indirect effect on innovation for firms without subsidies than firms with subsidies. If the proportion of firms with subsidies in one cluster becomes large, the patent activities of firms without subsidies increase faster than those of firms with subsidies. An increasing proportion of firms obtaining subsidies would encourage more firms without subsidies to participate in innovation activities. We also report the marginal effect in the quantity of truncated data in columns (5) and (6) and the marginal effect in the quantity of censored data in columns (8) and (9), which keep qualitatively unchanged.

[*Insert Table 3.14 here*]

3.9. Conclusions

Using panel data covering mainly unlisted firms in China over the period 1998-2008, we find that firms with more government subsidies are more likely to innovate. The estimation results also have some policy implications for China from the perspective of the incentive mechanism. First, since subsidies could play an active role in improving firms' innovation performance, governments should implement subsidy schemes that could motivate firms' innovation activities. Second, our study shows that the impact of government subsidies on innovation varies across firms with different types of ownership. Thus governments should further adjust the objective mechanism of subsidies. Specifically, more subsidies should be allocated to private firms instead of SOEs as the former has a strong demand for innovation and R&D funds. Third, considering our estimation results showing that subsidies have a stronger positive effect on innovation activities of more financially constrained firms compared to those of less financially healthier firms, governments should apply more subsidy policies to financially constrained firms, such as small firms, young firms, firms without political affiliation, firms without state shares, firms with a higher SA index. For example, in May 1999, the State Council of China approves a special government R&D program called 'Innovation fund for technology-based firms' which aims to 'facilitate and encourage the innovation activities of small and medium technology-based enterprises (SMTEs).' More policies similar to the program should be issued for financially constrained firms. Fourth, since the positive direct effect of subsidies on firms' innovation activities could be influenced by some other factors, such as industry external finance dependence, industry high-tech intensiveness, city financial development level, and city foreign direct investment level, governments need to be more considerate when they grant subsidies. Fifth, due to the positive indirect effect of subsidies on innovation for firms without subsidies, if governments hope to make more enterprises innovate, a certain amount of subsidies should be distributed to more firms to increase the proportion of firms with subsidies.

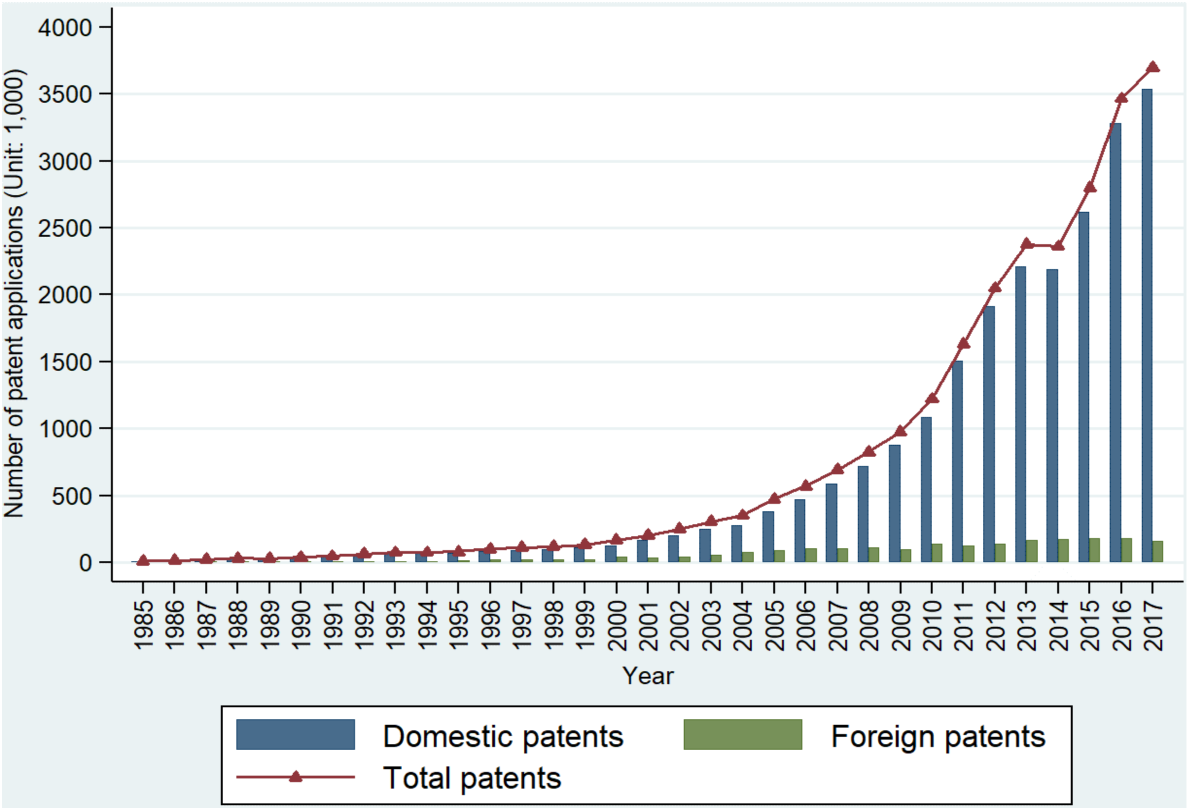


Figure 3.1. Number of China's patent applications from 1985 to 2017. Data Source: China's National Bureau of Statistics (NBS) – www.stats.gov.cn

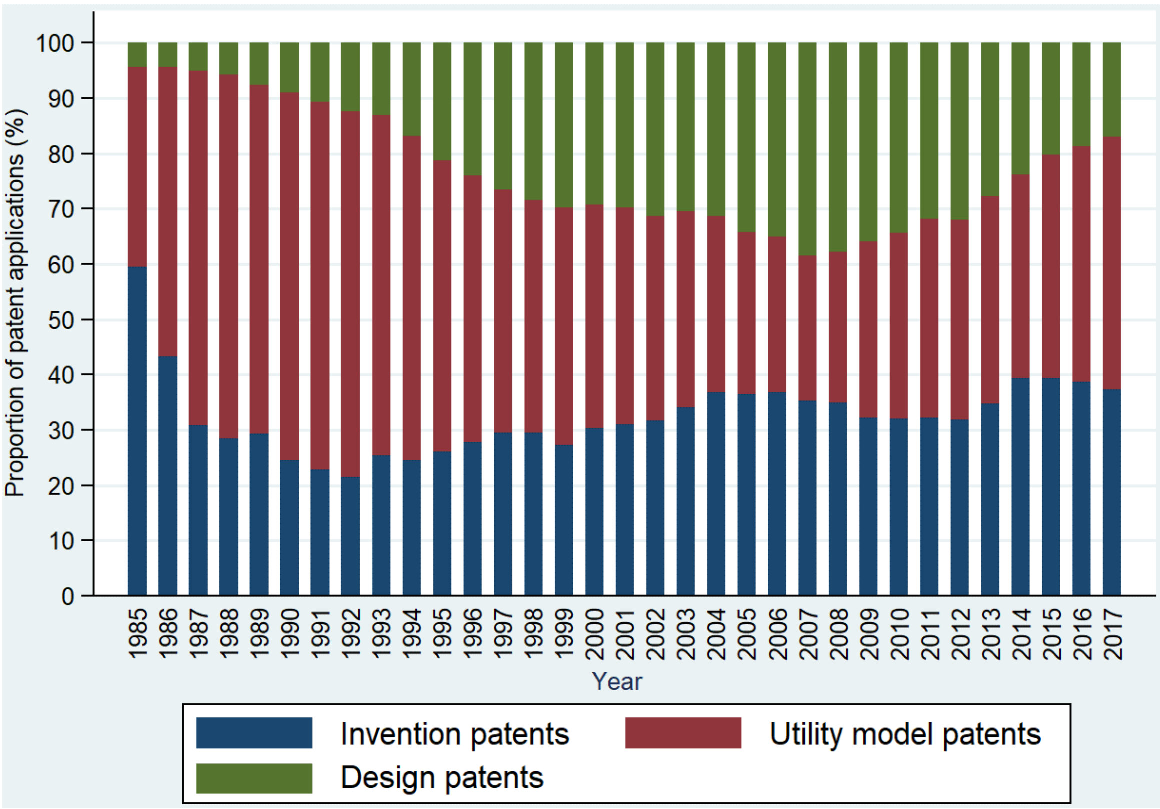


Figure 3.2. Proportion of three types of China's patent applications from 1985 to 2017. Data Source: China's National Bureau of Statistics (NBS) – www.stats.gov.cn

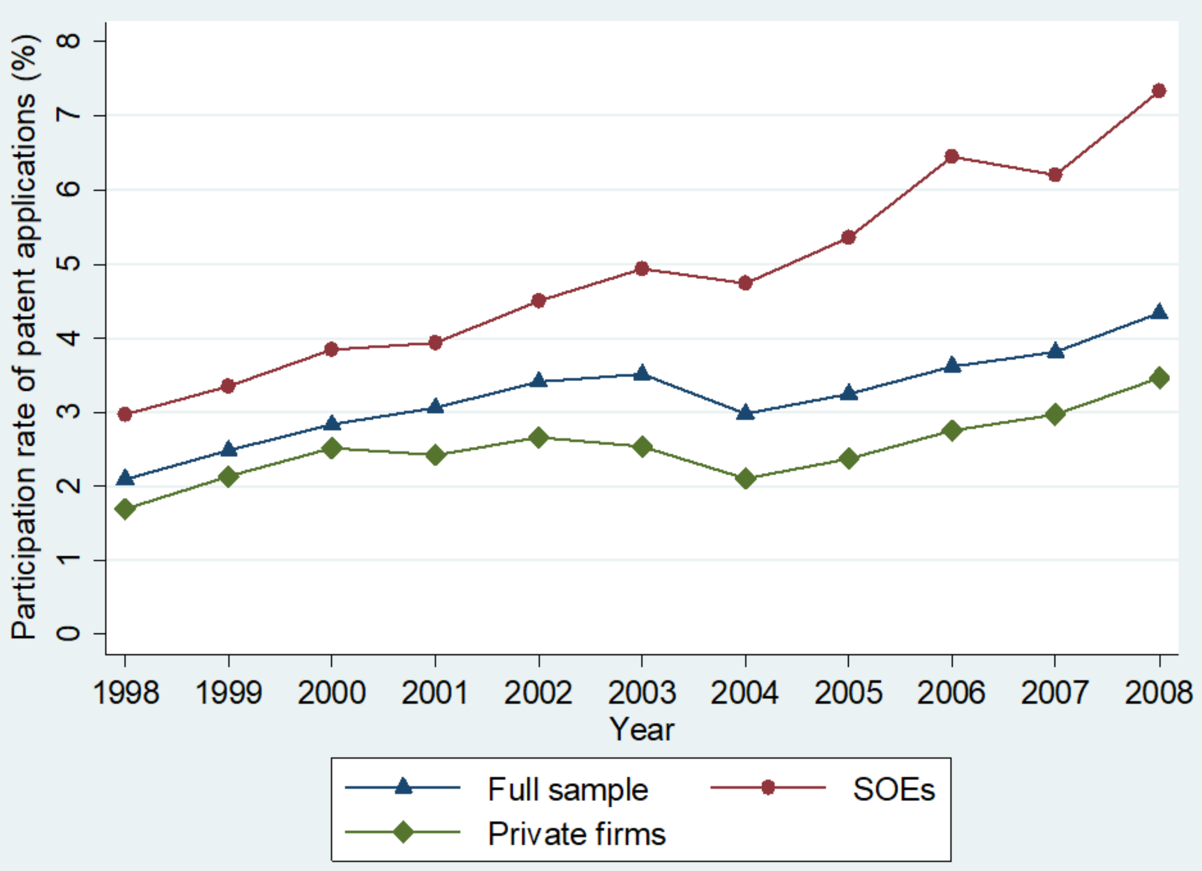


Figure 3.3. Participation rate of patent applications for firms in China from 1998 to 2008

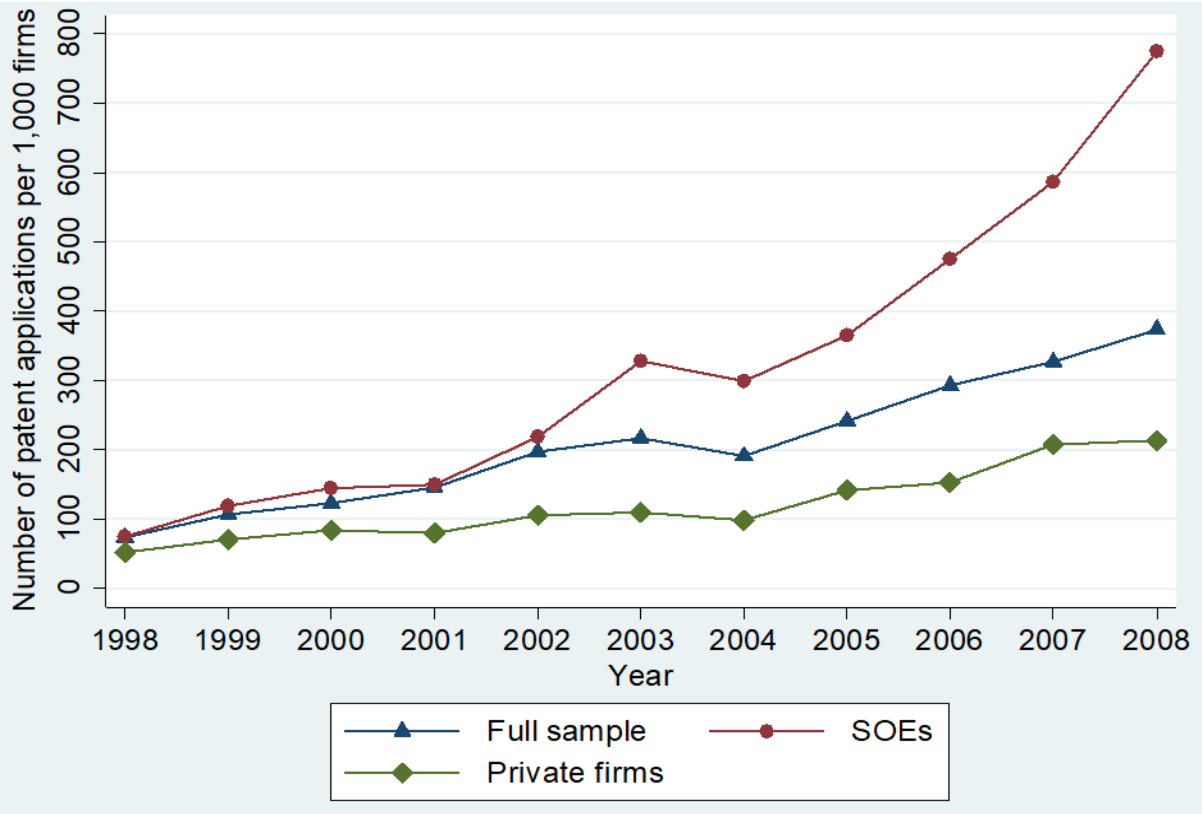


Figure 3.4. Number of patent applications per 1,000 firms in China from 1998 to 2008

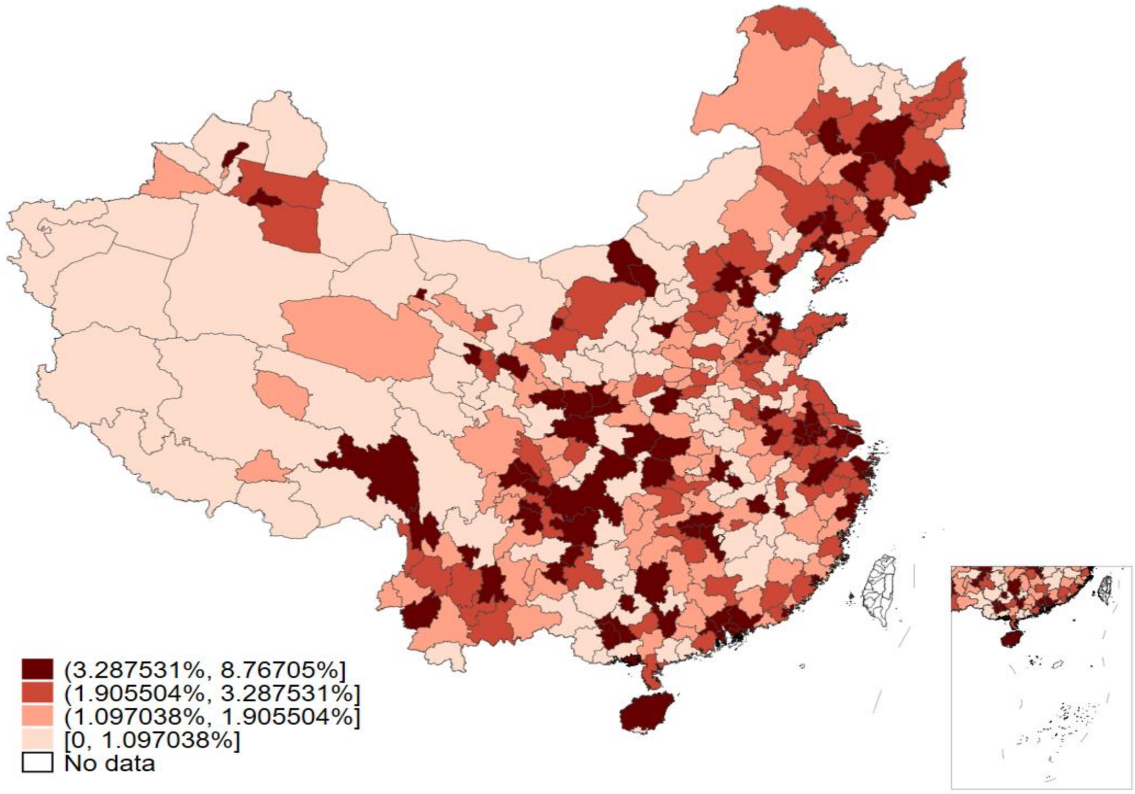


Figure 3.5. Average participation rate of patent applications for firms across prefecture-level administrative divisions in China from 1998 to 2008

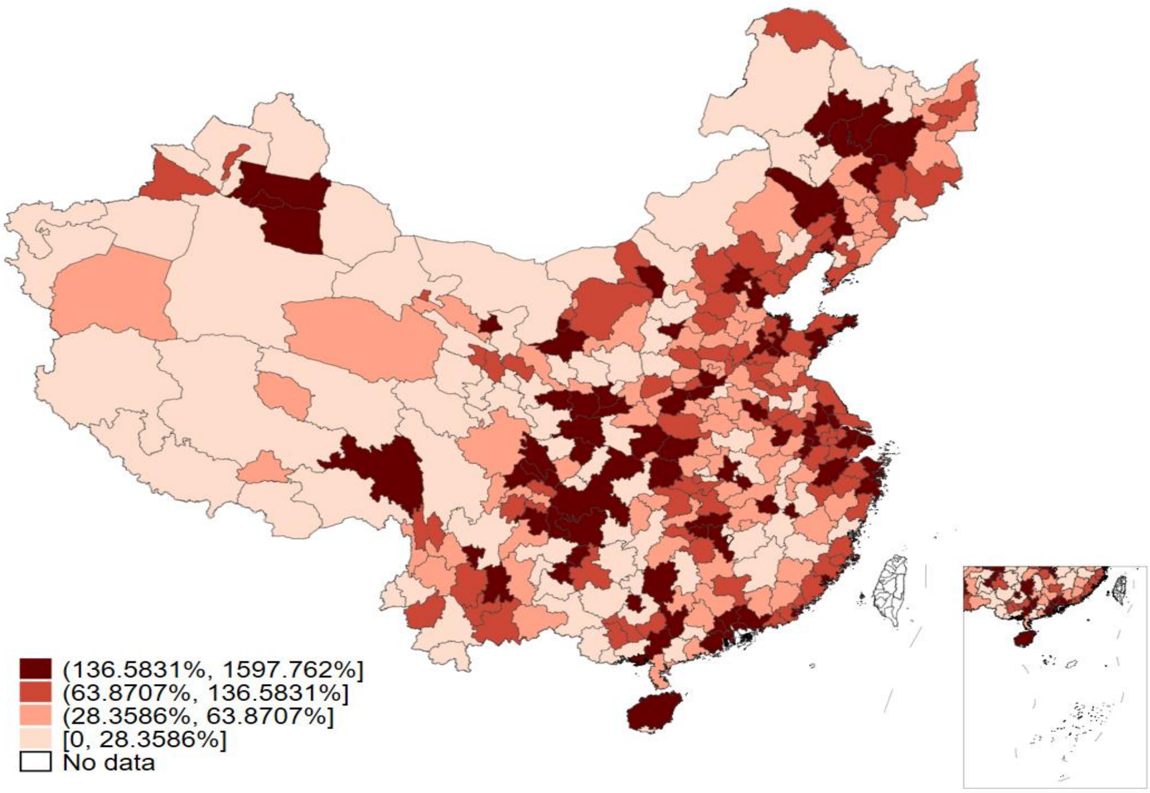


Figure 3.6. Average number of patent applications per 1,000 firms across prefecture-level administrative divisions in China from 1998 to 2008

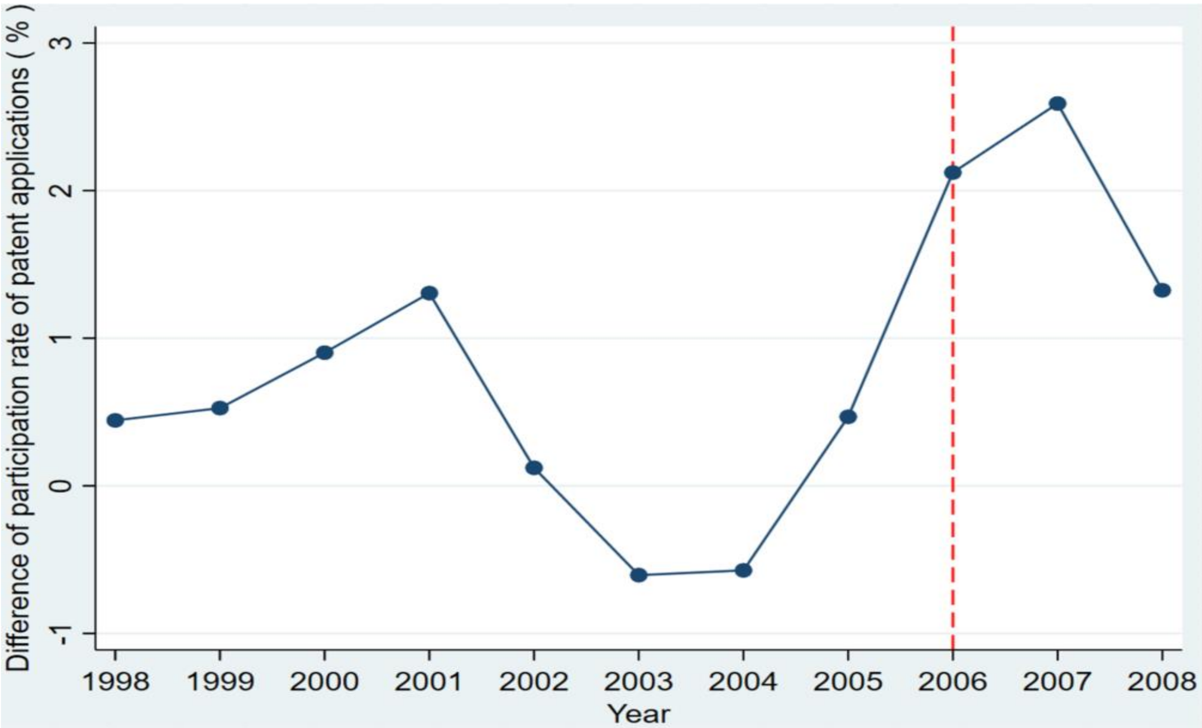


Figure 3.7. Trend line of the difference in the participation rate of patent applications from 1998 to 2008. Note: The figure illustrates the time trends of the difference in the participation rates of patent applications between the treatment group (i.e., firms in Zhangjiagang) and the control group (i.e., firms in the other county-level cities of Suzhou)

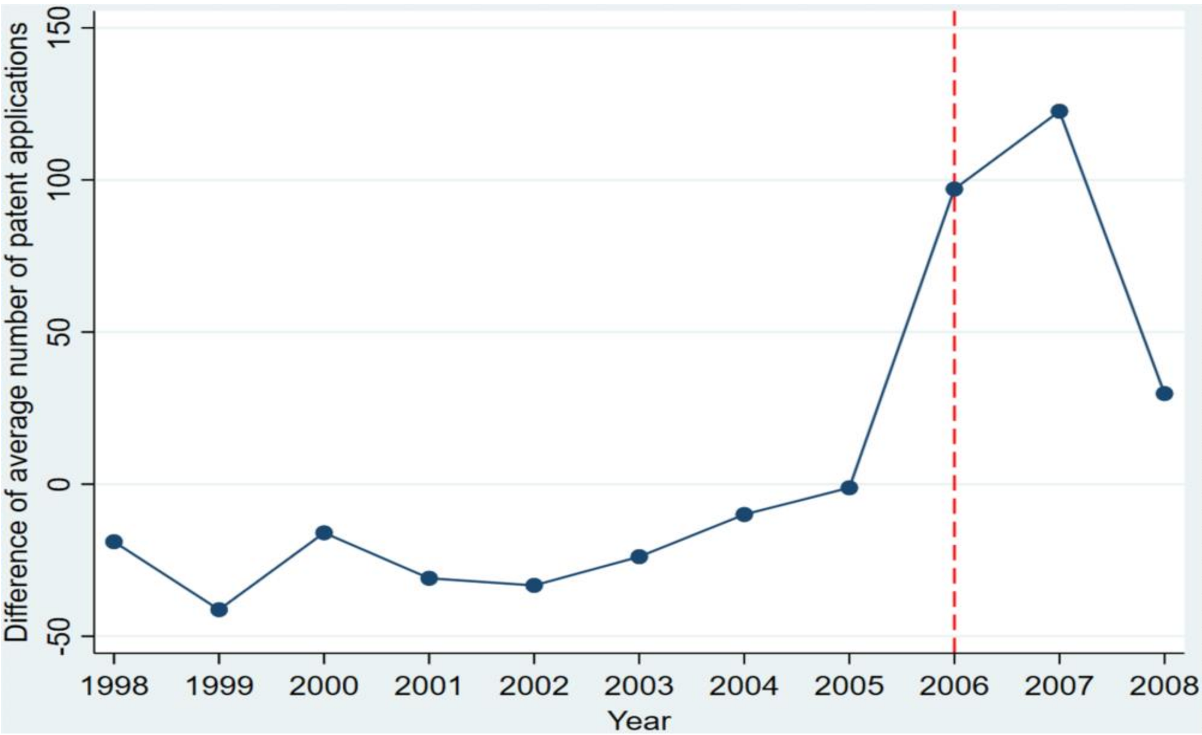


Figure 3.8. Trend line of the difference in the average number of patent applications from 1998 to 2008. Note: The figure illustrates the time trends of the difference in the average number of patent applications between the treatment group (i.e., firms in Zhangjiagang) and the control group (i.e., firms in the other county-level cities of Suzhou)

Table 3.1

Complete definitions of regression variables

$Log\ (Pat_{i,t} + 1)$	Natural logarithm of the number of patent applications plus one for firm i in the year t
$Log\ (Pat_{i,t-1} + 1)$	Natural logarithm of the number of patent applications plus one for firm i in the first lagged year of year t
$Log\ (Pat_{i,t-1} + 1)^2$	Squared natural logarithm of the number of patent applications plus one for firm i in the first lagged year of year t
$S_{i,t-1}$	The amount of sales to the amount of total assets for firm i in the first lagged year of year t
$Cf_{i,t-1}$	The amount of cash flows to the amount of total assets for firm i in the first lagged year of year t
$Dbt_{i,t-1}$	The amount of new long-term debts to the amount of total assets for firm i in the first lagged year of year t
$Sub_{i,t-1}$	The amount of total government subsidies to the amount of total assets for firm i in the first lagged year of year t
V_i	Firm fixed effects
V_t	Year fixed effects (2000 - 2008)
V_o	Ownership dummies (six types, SOE dummy is the benchmark)
V_j	Industry dummies (39 GB/T two-digit industry codes)
V_p	Geographical dummies (31 provincial administrative units except for Hong Kong, Macao and Taiwan)
$e_{i,j,o,p,t}$	Idiosyncratic error term

Table 3.2

Correlation analysis of regression variables

	$Log\ (Pat_{i,t}+1)$	$Sub_{i,t-1}$	$Log\ (Pat_{i,t-1}+1)$	$Log\ (Pat_{i,t-1}+1)^2$	$S_{i,t-1}$	$Cf_{i,t-1}$	$Dbt_{i,t-1}$
$Log\ (Pat_{i,t}+1)$	1.0000***						
$Sub_{i,t-1}$	0.0188***	1.0000***					
$Log\ (Pat_{i,t-1}+1)$	0.6220***	0.0173***	1.0000***				
$Log\ (Pat_{i,t-1}+1)^2$	0.5991***	0.0109***	0.8816***	1.0000***			
$S_{i,t-1}$	-0.0645***	-0.0708***	-0.0630***	-0.0385***	1.0000***		
$Cf_{i,t-1}$	-0.0092***	-0.0167***	-0.0147***	-0.0069***	0.4864***	1.0000***	
$Dbt_{i,t-1}$	0.0100***	-0.0011	0.0065***	0.0051***	-0.0064***	-0.0066***	1.0000***

Notes: This table reports the correlation indexes of the main regression variables in the baseline Euler equation (1). ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively. Complete definitions of all the variables and classification standards are in Table 3.1.

Table 3.3
Summary statistics - Sample means and medians (in parentheses)

	Full sample	Firms with patent applications	Firms without patent applications	SOEs	Private firms	*Diff1*	*Diff2*
Main regression variables							
$Log\ (Pat_{i,t}+1)$	0.068	1.454	0.000	0.083	0.054	0.000	0.000
	(0.000)	(1.099)	(0.000)	(0.000)	(0.000)		
$Sub_{i,t-1}$	0.186	0.260	0.182	0.277	0.168	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
$Log\ (Pat_{i,t-1}+1)$	0.059	0.760	0.024	0.074	0.044	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
$Log\ (Pat_{i,t-1}+1)^2$	0.111	1.689	0.033	0.137	0.077	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
$S_{i,t-1}$	189.053	125.652	192.177	86.131	222.384	0.000	0.000
	(130.496)	(98.057)	(132.829)	(57.829)	(158.964)		
$Cf_{i,t-1}$	9.700	8.645	9.752	4.377	10.596	0.000	0.000
	(6.073)	(6.326)	(6.059)	(3.123)	(6.427)		
$Dbt_{i,t-1}$	0.076	0.319	0.064	0.171	0.131	0.000	0.105
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Other firm-level variables							
Real total assets	115.370	776.732	82.779	397.523	43.140	0.000	0.000
	(20.006)	(94.073)	(18.940)	(60.817)	(13.990)		
Age	11.648	14.647	11.501	26.197	9.643	0.000	0.000
	(8.000)	(9.000)	(8.000)	(24.000)	(7.000)		
Political affiliation	73.986	66.575	74.352	39.784	82.002	0.000	0.000
	(90.000)	(90.000)	(90.000)	(40.000)	(90.000)		
Percentage of state shares	8.205	10.231	8.105	93.134	0.272	0.000	0.000
	(0.000)	(0.000)	(0.000)	(100.00)	(0.000)		
Region	1.355	1.320	1.357	1.780	1.330	0.000	0.000
	(1.000)	(1.000)	(1.000)	(2.000)	(1.000)		
Observations	1,110,382	52,147	1,058,235	90,124	446,572		

Notes: Real total assets are expressed in millions of yuan. All other variables except Log (number of patent applications), age, political affiliation and region are shown in percentage terms. All monetary variables are deflated using provincial ex-factory producer price indices. The last two columns present the p-values associated with the mean-equality test between the group of firms with patent applications and the group of firms without patent applications (*Diff1*) and between the group of SOEs and the group of private firms (*Diff2*). Complete definitions of all the variables and classification standards are in Table 3.1 and Appendix D.

Table 3.4

Modified baseline Euler equation (3.1) for the full sample

	Random-effects Tobit			Pooled Tobit		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.193***	0.721***	0.238***	0.185***	0.686***	0.255***
	[0.021]	[0.080]	[0.026]	[0.019]	[0.071]	[0.026]
$Log\ (Pat_{i,t-1} + 1)$	0.049***	0.184***	0.061***	0.100***	0.369***	0.137***
	[0.001]	[0.003]	[0.001]	[0.001]	[0.005]	[0.002]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.003***	-0.012***	-0.004***	-0.010***	-0.038***	-0.014***
	[0.000]	[0.001]	[0.000]	[0.001]	[0.002]	[0.001]
$S_{i,t-1}$	-0.009***	-0.032***	-0.011***	-0.009***	-0.033***	-0.012***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.032***	0.121***	0.040***	0.033***	0.124***	0.046***
	[0.002]	[0.007]	[0.002]	[0.002]	[0.007]	[0.002]
$Dbt_{i,t-1}$	0.015***	0.054***	0.018***	0.019***	0.071***	0.026***
	[0.003]	[0.010]	[0.003]	[0.003]	[0.010]	[0.004]
Rho	0.370	0.370	0.370			
Prob > chi2	0.000	0.000	0.000			
Pseudo R^2				0.226	0.226	0.226
Prob > F				0.000	0.000	0.000
Firms	337,637	337,637	337,637	337,637	337,637	337,637
Observations	1,110,382	1,110,382	1,110,382	1,110,382	1,110,382	1,110,382
Left-censored	1,058,235	1,058,235	1,058,235	1,058,235	1,058,235	1,058,235
Uncensored	52,147	52,147	52,147	52,147	52,147	52,147

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit and the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Pseudo R2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Prob > chi2 and Prob > F are the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.5
Modified baseline Euler equation (3.1) using the IV Tobit for the full sample

	$Sub_{i,t-1}$ is only instrumented by $Fin\_Inc_{c,t-1}$				$Sub_{i,t-1}$ is instrumented by $Fin\_Inc_{c,t-1}$ and $Med\_Sub_{c,t-1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-stage	Probability	Truncated	Censored	First-stage	Probability	Truncated	Censored
$Fin\_Inc_{c,t-1}$	0.003***				0.003***			
	[0.000]				[0.000]			
$Med\_Sub_{c,t-1}$					198.118***			
					[0.098]			
$Sub_{i,t-1}$		41.993***	153.064***	58.750***		7.591***	27.674***	10.619***
		[5.854]	[18.956]	[8.676]		[1.217]	[4.334]	[1.723]
$Log\ (Pat_{i,t-1}+1)$	0.059***	0.102***	0.371***	0.142***	0.059***	0.102***	0.372***	0.143***
	[0.000]	[0.001]	[0.010]	[0.001]	[0.000]	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1}+1)^2$	-0.010***	-0.010***	-0.038***	-0.014***	-0.010***	-0.010***	-0.038***	-0.014***
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.030***	-0.009***	-0.032***	-0.012***	-0.030***	-0.009***	-0.033***	-0.013***
	[0.000]	[0.001]	[0.005]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]
$Cf_{i,t-1}$	0.220***	0.034***	0.123***	0.047***	0.219***	0.033***	0.122***	0.047***
	[0.000]	[0.011]	[0.041]	[0.014]	[0.000]	[0.003]	[0.012]	[0.004]
$Dbt_{i,t-1}$	0.013	0.021***	0.076***	0.029***	0.013	0.021***	0.076***	0.029***
	[0.000]	[0.003]	[0.011]	[0.004]	[0.000]	[0.003]	[0.011]	[0.004]
F − statistics	418.100				418.190			
Adjusted R^2	0.036				0.036			
Prob > chi2		0.000	0.000	0.000		0.000	0.000	0.000
Wald test of exogeneity (p − value)		0.000	0.000	0.000		0.000	0.000	0.000
Anderson − Rubin (p − value)		0.000	0.000	0.000		0.000	0.000	0.000
Firms	306,659	306,659	306,659	306,659	306,659	306,659	306,659	306,659
Observations	948,873	948,873	948,873	948,873	948,873	948,873	948,873	948,873
Left-censored	902,183	902,183	902,183	902,183	902,183	902,183	902,183	902,183
Uncensored	46,690	46,690	46,690	46,690	46,690	46,690	46,690	46,690

Notes: This table reports the estimation results of the modified baseline Euler equation (3.1) using the IV Tobit. Columns (1) and (5) report coefficients (in percentage) of the first-stage results. Columns (2) to (4) and columns (6) to (8) report the marginal effects of the second-stage results. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Wald test of exogeneity is distributed as chi-square under the null hypothesis of exogeneity. Anderson-Rubin is under the null hypothesis that the minimum canonical correlation is zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.6

Modified baseline Euler equation (3.1) of the quasi-natural experiment for the subsample of firms in Suzhou

	(1)	(2)	(3)	(4)	(5)	(6)
$Treat * Post$	0.047***	0.080***	0.079***		0.018	0.004
	[0.009]	[0.015]	[0.015]		[0.017]	[0.010]
$Treat$	0.014**	0.029***		0.031***	0.006	0.028***
	[0.006]	[0.009]		[0.009]	[0.007]	[0.008]
$Post$	0.049***	0.041***			0.012**	0.040***
	[0.002]	[0.004]			[0.005]	[0.004]
$Treat * Year$ 2001				-0.001		
				[0.023]		
$Treat * Year$ 2002				0.007		
				[0.025]		
$Treat * Year$ 2003				-0.024		
				[0.018]		
$Treat * Year$ 2004				-0.006		
				[0.020]		
$Treat * Year$ 2005				0.007		
				[0.021]		
$Treat * Year$ 2006				0.055**		
				[0.022]		
$Treat * Year$ 2007				0.111***		
				[0.027]		
$Treat * Year$ 2008				0.059**		
				[0.026]		
Other control variables	No	Yes	Yes	Yes	Yes	Yes
Rho	0.681	0.334	0.357	0.359	0.164	0.323
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	21,506	8,740	8,740	8,740	4,576	8,740
Observations	68,065	30,180	30,180	30,180	12,992	30,180
Left-censored	65,214	28,362	28,362	28,362	12,421	28,362
Uncensored	2,851	1,818	1,818	1,818	571	1,818

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Industry, location and ownership dummies are included in all specifications but not reported [except column (1)]. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.7

Modified augmented Euler equation (3.1) the full sample with contemporaneous terms

	(1)	(2)	(3)
	Probability	Truncated	Censored
$Sub_{i,t}$	0.191***	0.704***	0.229***
	[0.028]	[0.104]	[0.034]
$Sub_{i,t-1}$	0.084***	0.311***	0.101***
	[0.028]	[0.104]	[0.034]
SUM ($Sub_{i,t}$ and $Sub_{i,t-1}$)	0.275***	1.015***	0.331***
	[0.028]	[0.104]	[0.034]
$Log\ (Pat_{i,t-1} + 1)$	0.053***	0.196***	0.064***
	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.003***	-0.012***	-0.004***
	[0.000]	[0.001]	[0.000]
$S_{i,t}$	-0.005***	-0.019***	-0.006***
	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.005***	-0.018***	-0.006***
	[0.000]	[0.001]	[0.000]
$Cf_{i,t}$	0.020***	0.075***	0.024***
	[0.003]	[0.009]	[0.003]
$Cf_{i,t-1}$	0.020***	0.073***	0.024***
	[0.003]	[0.010]	[0.003]
$Dbt_{i,t}$	0.016***	0.058***	0.019***
	[0.003]	[0.011]	[0.004]
$Dbt_{i,t-1}$	0.018***	0.068***	0.022***
	[0.003]	[0.011]	[0.004]
Rho	0.335	0.335	0.335
Prob > chi2	0.000	0.000	0.000
Firms	287,452	287,452	287,452
Observations	868,294	868,294	868,294
Left-censored	828,868	828,868	828,868
Uncensored	39,426	39,426	39,426

Notes: This table reports the marginal effects of the modified augmented Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). SUM ($Sub_{i,t}$ and $Sub_{i,t-1}$) is the sum of the marginal effects of the contemporaneous subsidy variable $Sub_{i,t}$ and the lagged subsidy variable $Sub_{i,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.8

Modified baseline Euler equation (3.1) for the full sample: using alternative measurements of innovation activities (new product output value / total assets and R&D expenditure / total assets, labelled as Np and Rd)

	New product output value			R&D expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.083***	0.047***	0.024***	0.406***	0.006***	0.004***
	[0.025]	[0.014]	[0.007]	[0.047]	[0.001]	[0.000]
$Np_{i,t-1}(Rd_{i,t-1})$	0.607***	0.346***	0.177***	27.790***	0.390***	0.253***
	[0.004]	[0.002]	[0.001]	[0.197]	[0.003]	[0.002]
${Np_{i,t-1}}^2(Rd_{i,t-1})^2$	-0.481***	-0.274***	-0.140***	-572.315***	-8.038***	-5.211***
	[0.004]	[0.003]	[0.001]	[5.977]	[0.086]	[0.058]
$S_{i,t-1}$	-0.010***	-0.006***	-0.003***	-0.014***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.018***	0.010***	0.005***	0.062***	0.001***	0.001***
	[0.002]	[0.001]	[0.001]	[0.004]	[0.000]	[0.000]
$Dbt_{i,t-1}$	-0.001	-0.001	-0.000	0.019***	0.000***	0.000***
	[0.003]	[0.002]	[0.001]	[0.006]	[0.000]	[0.000]
Rho	0.270	0.270	0.270	0.286	0.286	0.286
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	327,550	327,550	327,550	252,311	252,311	252,311
Observations	888,928	888,928	888,928	514,380	514,380	514,380
Left-censored	829,733	829,733	829,733	449,395	449,395	449,395
Uncensored	59,195	59,195	59,195	64,985	64,985	64,985

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Np_{i,t}$ or $Rd_{i,t}$ is a censored variable that takes its real value if the firm has a new product output value or R&D expenditure (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.9

Modified baseline Euler equation (3.1) of additional robustness tests for the full sample

	(1) Invention patents	(2) Zero-inflated Poisson	(3) Log of financial variables	(4) Data excluding the year 2008
	Censored	/	Censored	Censored
$Sub_{i,t-1}$	0.134***	0.162***	0.003***	0.193***
	[0.012]	[0.024]	[0.000]	[0.027]
$Log\ (Pat_{i,t-1}+1)$	0.062***	0.030***	0.084***	0.063***
	[0.001]	[0.001]	[0.001]	[0.001]
$Log\ (Pat_{i,t-1}+1)^2$	-0.006***	-0.005***	-0.011***	-0.004***
	[0.001]	[0.000]	[0.000]	[0.000]
$S_{i,t-1}$	-0.006***	-0.011***	0.013***	-0.010***
	[0.000]	[0.000]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.026***	0.030***	0.006***	0.035***
	[0.001]	[0.002]	[0.000]	[0.003]
$Dbt_{i,t-1}$	0.014***	0.011***	0.001***	0.017***
	[0.002]	[0.003]	[0.000]	[0.003]
Rho	0.234	0.190	0.203	0.228
Prob > chi2	0.000	0.000	0.000	0.000
Firms	337,637	335,620	305,876	297,534
Observations	1,110,382	1,089,180	782,094	905,590
Left-censored	1,088,763	1,055,302	751,291	865,272
Uncensored	21,619	33,878	30,803	40,318

Notes: This table reports the estimation results of the modified baseline Euler equation (3.1) of additional robustness tests. In columns (1), (3) and (4) we report marginal effects in the quantity of censored data and the dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). In column (2) we report marginal effects on the expected value of the number of patent applications concerning the random effect and the dependent variable is the number of patent applications per firm ($Pat_{i,t}$). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit and Random-effects Poisson regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.10

Modified baseline Euler equation (3.1) for the sample of SOEs and private firms

	Probability		Truncated		Censored	
	(1) SOEs	(2) Private	(3) SOEs	(4) Private	(5) SOEs	(6) Private
$Sub_{i,t-1}$	0.068	0.294***	0.196	1.237***	0.081	0.375***
	[0.074]	[0.030]	[0.213]	[0.132]	[0.088]	[0.039]
Diff1 (p − value)	(0.000)***		(0.000)***		(0.000)***	
$Log\ (Pat_{i,t-1} + 1)$	0.082***	0.062***	0.234***	0.260***	0.098***	0.079***
	[0.003]	[0.001]	[0.009]	[0.009]	[0.004]	[0.002]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.006***	-0.006***	-0.018***	-0.025***	-0.007***	-0.008***
	[0.001]	[0.000]	[0.002]	[0.002]	[0.001]	[0.000]
$S_{i,t-1}$	-0.013***	-0.007***	-0.036***	-0.030***	-0.015***	-0.009***
	[0.001]	[0.000]	[0.003]	[0.001]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.109***	0.024***	0.312***	0.100***	0.130***	0.030***
	[0.009]	[0.003]	[0.026]	[0.012]	[0.011]	[0.004]
$Dbt_{i,t-1}$	0.022**	0.020***	0.064**	0.083***	0.026**	0.025***
	[0.009]	[0.004]	[0.025]	[0.017]	[0.010]	[0.005]
Rho	0.273	0.234	0.273	0.234	0.273	0.234
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	32,418	177,573	32,418	177,573	32,418	177,573
Observations	95,650	435,205	95,650	435,205	95,650	435,205
Left-censored	90,015	418,145	90,015	418,145	90,015	418,145
Uncensored	5,635	17,060	5,635	17,060	5,635	17,060

Notes: This table reports the marginal effects of the modified baseline Euler equation (1) using the Random-effects Tobit. We report marginal effects in the quantity of censored data and the dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Diff1 (p-value) is the p-value for the difference in the marginal effects of $Sub_{i,t-1}$ between SOEs and private firms. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.11

Modified baseline Euler equation (3.1) for the heterogeneity on firms' financial constraints

	Size		Age		Political affiliation		State shares		SA	
	(1) Small	(2) Large	(3) Young	(4) Mature	(5) Without	(6) With	(7) Without	(8) With	(9) Low	(10) High
	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored
$Sub_{i,t-1}$	0.212***	0.152***	0.305***	0.203***	0.446***	0.047	0.244***	0.154*	0.173***	0.204***
	[0.044]	[0.008]	[0.035]	[0.037]	[0.03]	[0.038]	[0.028]	[0.087]	[0.009]	[0.042]
Diff1 $(\mathrm{p-value})$	(0.000)***		(0.000)***		(0.000)***		(0.000)***		(0.000)***	
$Log\ (Pat_{i,t-1}+1)$	0.071***	0.173***	0.123***	0.150***	0.085***	0.073***	0.067***	0.099***	0.179***	0.072***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.003]	[0.003]	[0.003]
$Log\ (Pat_{i,t-1}+1)^2$	-0.013***	-0.016***	-0.014***	-0.014***	-0.008***	-0.005***	-0.005***	-0.006***	-0.017***	-0.013***
	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
$S_{i,t-1}$	-0.006***	-0.019***	-0.010***	-0.014***	-0.009***	-0.014***	-0.010***	-0.016***	-0.012***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
$Cf_{i,t-1}$	0.005***	0.045***	0.033***	0.062***	0.033***	0.065***	0.037***	0.132***	0.078***	0.003***
	[0.001]	[0.004]	[0.003]	[0.004]	[0.003]	[0.004]	[0.002]	[0.010]	[0.004]	[0.001]
$Dbt_{i,t-1}$	0.005***	0.033***	0.028***	0.025***	0.019***	0.024***	0.018***	0.031***	0.034***	0.009***
	[0.000]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.003]	[0.010]	[0.006]	[0.000]
Rho	0.174	0.232	0.212	0.234	0.241	0.329	0.325	0.296	0.222	0.181
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	195,972	209,831	231,066	185,465	232,662	159,139	313,605	41,707	198,370	202,027
Observations	457,705	652,677	520,124	589,009	635,312	475,070	982,444	124,176	658,374	452,008
Left-censored	448,993	609,242	499,797	557,344	608,397	449,838	938,790	115,800	614,440	443,795
Uncensored	8,712	43,435	20,327	31,665	26,915	25,232	43,654	8,376	43,934	8,213

Notes: This table only reports the marginal effects in the quantity of censored data of the modified baseline Euler equation (1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Diff1 (p-value) is the p-value for the difference in the marginal effects of $Sub_{i,t-1}$ between two groups for one comparison. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.12

Modified baseline Euler equation (3.1) for the full sample with industry-level EFD and High tech-intensiveness

	EFD			High tech-intensiveness		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.158***	0.583***	0.190***	0.146***	0.544***	0.179***
	[0.024]	[0.087]	[0.028]	[0.023]	[0.088]	[0.029]
$Sub_{i,t-1} * EFD_j$	-0.513***	-1.888***	-0.615***			
	[0.138]	[0.507]	[0.165]			
EFD_j	0.012***	0.045***	0.015***			
	[0.002]	[0.007]	[0.002]			
$Sub_{i,t-1} * High - tech_{j,t-1}$				0.292***	1.088***	0.359***
				[0.059]	[0.218]	[0.072]
$High - tech_{j,t-1}$				0.01***	0.060***	0.020***
				[0.001]	[0.004]	[0.001]
$Log\ (Pat_{i,t-1} + 1)$	0.054***	0.198***	0.064***	0.049***	0.183***	0.060***
	[0.001]	[0.003]	[0.001]	[0.001]	[0.003]	[0.001]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.003***	-0.013***	-0.004***	-0.003***	-0.012***	-0.004***
	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$S_{i,t-1}$	-0.008***	-0.031***	-0.010***	-0.009***	-0.032***	-0.011***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
$Cf_{i,t-1}$	0.031***	0.113***	0.037***	0.032***	0.119***	0.039***
	[0.002]	[0.008]	[0.003]	[0.002]	[0.007]	[0.002]
$Dbt_{i,t-1}$	0.015***	0.054***	0.018***	0.015***	0.054***	0.018***
	[0.003]	[0.010]	[0.003]	[0.003]	[0.010]	[0.003]
Rho	0.332	0.332	0.332	0.371	0.371	0.371
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Firms	292,722	292,722	292,722	337,637	337,637	337,637
Observations	878,713	878,713	878,713	1,110,382	1,110,382	1,110,382
Left-censored	838,638	838,638	838,638	1,058,235	1,058,235	1,058,235
Uncensored	40,075	40,075	40,075	52,147	52,147	52,147

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.13
Modified baseline Euler equation (3.1) for the full sample with city-level financial development and foreign direct investment

	Panel A: financial development								
	Loans			Deposits			Savings		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Truncated	Censored	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.250***	0.902***	0.328***	0.252***	0.910***	0.331***	0.242***	0.871***	0.317***
	[0.027]	[0.098]	[0.036]	[0.027]	[0.097]	[0.035]	[0.026]	[0.094]	[0.034]
$Sub_{i,t-1} * Fin-dev_{c,t-1}$	-0.082*	-0.294*	-0.107**	-0.074**	-0.265**	-0.097**	-0.285**	-1.028**	-0.374**
	[0.044]	[0.160]	[0.058]	[0.030]	[0.108]	[0.039]	[0.118]	[0.426]	[0.155]
$Fin-dev_{c,t-1}$	0.010***	0.035***	0.013***	0.008***	0.027***	0.010***	0.002	0.006	0.002
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.005]	[0.002]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	0.240	0.240	0.240	0.239	0.239	0.239	0.238	0.238	0.238
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	277,534	277,534	277,534	277,534	277,534	277,534	277,534	277,534	277,534
Observations	784,847	784,847	784,847	784,847	784,847	784,847	784,847	784,847	784,847
Left-censored	745,600	745,600	745,600	745,600	745,600	745,600	745,600	745,600	745,600
Uncensored	39,247	39,247	39,247	39,247	39,247	39,247	39,247	39,247	39,247
	Panel B: foreign direct investment								
	New contracts signed			Agreed investment			Actual investment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Truncated	Censored	Probability	Truncated	Censored	Probability	Truncated	Censored
$Sub_{i,t-1}$	0.225***	0.823***	0.280***	0.216***	0.792***	0.269***	0.214***	0.782***	0.265***
	[0.023]	[0.084]	[0.029]	[0.023]	[0.084]	[0.029]	[0.023]	[0.084]	[0.028]
$Sub_{i,t-1} * For-inv_{c,t-1}$	-0.030**	-0.108**	-0.037**	-0.508*	-1.858*	-0.631*	-1.011	-3.701	-1.256
	[0.012]	[0.044]	[0.015]	[0.281]	[1.028]	[0.349]	[0.631]	[2.308]	[0.783]
$For-inv_{c,t-1}$	0.004***	0.015***	0.005***	0.027***	0.099***	0.034***	0.051***	0.186***	0.063***
	[0.000]	[0.001]	[0.000]	[0.003]	[0.011]	[0.004]	[0.006]	[0.024]	[0.008]
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rho	0.361	0.361	0.361	0.361	0.361	0.361	0.362	0.362	0.362
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	314,677	314,677	314,677	314,844	314,844	314,844	315,118	315,118	315,118
Observations	1,011,225	1,011,225	1,011,225	1,012,299	1,012,299	1,012,299	1,013,293	1,013,293	1,013,293
Left-censored	962,103	962,103	962,103	963,144	963,144	963,144	964,122	964,122	964,122
Uncensored	49,122	49,122	49,122	49,155	49,155	49,155	49,171	49,171	49,171

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Table 3.14
Modified baseline Euler equation (3.1) with the variable of $Sub - Propor_{j,t-1}$

	Probability			Truncated			Censored		
	(1) Full sample	(2) $Sub_{i,t-1}$=0	(3) $Sub_{i,t-1}$>0	(4) Full sample	(5) $Sub_{i,t-1}$=0	(6) $Sub_{i,t-1}$>0	(7) Full sample	(8) $Sub_{i,t-1}$=0	(9) $Sub_{i,t-1}$>0
$Sub_{i,t-1}$	0.162***			0.666***			0.203***		
	[0.025]			[0.097]			[0.034]		
$Sub - Propor_{j,t-1}$	0.027***	0.006***	0.003	0.101***	0.024***	0.009	0.037***	0.007***	0.005
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Diff1 (p − value)		(0.000)***			(0.000)***			(0.000)***	
$Sub_{i,t-1} * Sub - Propor_{j,t-1}$	-0.654***			-2.691***			-0.886***		
	[0.001]			[0.003]			[0.001]		
$Log\ (Pat_{i,t-1} + 1)$	0.099***	0.087***	0.159***	0.366***	0.366***	0.390***	0.136***	0.115***	0.244***
	[0.001]	[0.001]	[0.002]	[0.002]	[0.003]	[0.000]	[0.001]	[0.001]	[0.003]
$Log\ (Pat_{i,t-1} + 1)^2$	-0.010***	-0.009***	-0.014***	-0.037***	-0.039***	-0.034***	-0.014***	-0.012***	-0.021***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]
$S_{i,t-1}$	-0.009***	-0.007***	-0.015***	-0.032***	-0.028***	-0.037***	-0.012***	-0.009***	-0.023***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]	[0.000]	[0.000]	[0.001]
$Cf_{i,t-1}$	0.034***	0.024***	0.109***	0.125***	0.100***	0.268***	0.046***	0.031***	0.167***
	[0.002]	[0.002]	[0.007]	[0.007]	[0.007]	[0.018]	[0.002]	[0.002]	[0.011]
$Dbt_{i,t-1}$	0.019***	0.012***	0.053***	0.070***	0.052***	0.130***	0.026***	0.016***	0.81***
	[0.003]	[0.003]	[0.010]	[0.010]	[0.011]	[0.024]	[0.004]	[0.004]	[0.015]
Rho	0.228	0.211	0.239	0.228	0.211	0.239	0.228	0.211	0.239
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firms	337,637	318,696	73,952	337,637	318,696	73,952	337,637	318,696	73,952
Observations	1,110,382	950,926	159,456	1,110,382	950,926	159,456	1,110,382	950,926	159,456
Left-censored	1,058,235	915,194	143,041	1,058,235	915,194	143,041	1,058,235	915,194	143,041
Uncensored	52,147	35,732	16,415	52,147	35,732	16,415	52,147	35,732	16,415

Notes: This table reports the marginal effects of the modified baseline Euler equation (3.1) using the Random-effects Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $Sub_{i,t-1} * Sub - Propor_{j,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $Sub_{i,t-1}$ evaluated at two infinitesimally close values of $Sub - Propor_{j,t-1}$ (the mean and the mean plus 0.001), divided by the difference between these two values (i.e. 0.001). Diff1 (p-value) is the p-value for the difference in the marginal effects of $Sub - Propor_{j,t-1}$ between two comparative groups. Heteroscedasticity-consistent standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively. Time, industry, location and ownership dummies are included in all specifications but not reported. Rho is the per cent contribution to the total variance of the panel-level variance component in the Random-effects Tobit regressions. Prob > chi2 is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Complete definitions of all variables and classification standards are in Table 3.1 and Appendix D.

Appendix

Appendix A. Description of the three types of patents in China

The three types of China's patents are different in applicable targets, protection periods and approval procedures. First, according to China's patent law, invention patents are defined as new technical proposals on products, methods or their improvements; utility model patents are defined as new technical proposals on product shape, product structure or their combination; design patents are defined as new aesthetic designs of product shape, product pattern, product colour or their combination. Second, the amendment to China's patent law in 1992 extends the protection duration for invention patents from 15 to 20 years and for utility model patents and design patents from 5 to 10 years, which is also a major requirement from the 'Agreement On Trade-related Aspects of Intellectual Property Right' (TRIPS) to ensure benefits of patent applications. Third, it usually takes about 2 to 3 years for the SIPO to process an invention patent application, while the corresponding approval cycle for a utility model patent application and a design patent application is about 6 months. Besides that, the approval procedures for an innovation patent must meet the high requirement of 'novelty, inventiveness, and practical applicability'. However, the approval procedures for a utility model patent and a design patent are simpler, and thus it is difficult to determine whether they have 'novelty, inventiveness, and practical applicability'.

Appendix B. NBS firm-level panel data

In principle, the sample coverage of the NBS firm-level data should be identical to that of the *China Statistical Yearbook*, or the discrepancies are relatively small. Thus, we compare the NBS-firm level data with the *China Statistical Yearbook* 2009 to verify the data reliability, and Table 3.A1 reports the comparison results. The statistics for all years except 1998, 2004 and 2008 are identical, confirming that the NBS-firm level data in our paper are also the basis for the numbers reported in the *China Statistical Yearbook*. For the year 1998, the number of firms in the NBS firm-level data is more than that recorded in the *China Statistical Yearbook,* while the discrepancy is quite small (only 38). Additionally, the data in 1998 is used to construct lagged values of the independent variables in our models, and thus the period of our estimation sample does not cover the year 1998. The data in the year 2004 contains the information of some SOEs that are not 'above-scale' enterprises, so the number of firms in 2004 of the NBS firm-level data is more than that recorded in the *China Statistical Yearbook*. In the section of our data process, we have dropped the observations with sales of less than 5 million Chinese Yuan to avoid the influence of no 'above-scale' enterprises. The number of firms in the year 2008 is less than 10,000 than that recorded in the *China Statistical Yearbook,* so we also delete the data in the year 2008 to estimate again for robustness test and the results keep qualitatively consistent. Table 3.A2 shows the structure of the unbalanced panel after the data process.

Table 3.A1

Comparison of the NBS firm-level data with the *China Statistical Yearbook* 2009

Year	NBS firm-level data	*China Statistical Yearbook*
1998	165,118	165,080
1999	162,033	162,033
2000	162,885	162,885
2001	171,256	171,256
2002	181,557	181,557
2003	196,222	196,222
2004	279,092	276,474
2005	271,835	271,835
2006	301,961	301,961
2007	336,768	336,768
2008	412,212	426,113
Total	2,640,939	2,652,184

Table 3.A2

Structure of the unbalanced panel

Year	Number of observations	Per cent (%)	Cumulative (%)
1998	123,544	5.21	5.21
1999	121,014	5.10	10.30
2000	125,585	5.29	15.59
2001	137,985	5.81	21.41
2002	150,861	6.36	27.76
2003	172,869	7.28	35.05
2004	262,145	11.04	46.09
2005	258,969	10.91	57.00
2006	290,526	12.24	69.24
2007	330,185	13.91	83.16
2008	399,805	16.84	100.00
Total	2,373,488	100.00	

Number of years per firm	Number of observations	Per cent (%)	Cumulative (%)
1	196,037	8.26	8.26
2	216,454	9.12	17.38
3	257,418	10.85	28.22
4	242,812	10.23	38.45
5	419,360	17.67	56.12
6	228,102	9.61	65.73
7	157,465	6.63	72.37
8	168,976	7.12	79.49
9	106,038	4.47	83.96
10	111,920	4.72	88.67
11	268,906	11.33	100.00
Total	2,373,488	100.00	

Appendix C. China's industry classification standard and its revision in 2002

China's industry sector code is made up of four digits. The first two digits are GB/T two-digit sector codes, the first three digits are GB/T three-digit sector codes, and all four digits are GB/T four-digit sector codes. In 2002, China revised its industrial classification standard issued in 1994 to keep consistent with the regulations of the WTO. The revision of the industry classification in 2002 has little impact on two-digit codes but more on three-digit codes and four-digit codes. The adjustments to four-digit sector codes have four types: first, some sectors just change their codes; second, some sectors are broken down into new ones; third, some sectors are merged with others into a new sector; fourth, some sectors are broken down into new sectors some of which are merged with other sectors into a new one. We manually adjust all four-digit sector codes to the revision in 2002. After the adjustment, we extract the first three digits and first two digits respectively to get the adjusted three-digit sector codes and the adjusted two-digit sector codes. Finally, we get 525 GB/T four digit-sector codes, 191 GB/T three digit-sector codes and 39 GB/T two digit-sector codes. All industry dummy variables are constructed on the adjusted sector codes. We drop observations in the sectors that disappeared or transferred to other non-manufacturing sectors after the revision in 2002. The proportion of these observations in the transferred and disappeared is low, only approximately 0.290%.

Since in our regression models we include the industry dummy variables based on GB/T two digit-code, we show the detailed description of all two-digit sectors in Table 3.A3. We can find all two-digit sectors keep the same codes after the revision in 2002 except the sector of timber and bamboo wood with the code of 12 (which is removed from the scope of manufacturing industries) and the sector of Waste Material Recycling Processing with the code of 43 (which is moved to the scope of manufacturing industries).

Table 3.A3
Description of GB/T two-digit industries

GB/T two-Digit Industry name	Two-Digit codes (1994-2002)	Two-Digit codes (1994-2002)
Coal Mining & Dressing	06	06
Petroleum & Natural Gas Extraction	07	07
Ferrous Metals Mining & Dressing	08	08
Non-Ferrous Metals Mining & Dressing	09	09
Non-metal Minerals Mining & Dressing	10	10
Mining of other Mineral	11	11
Timber and bamboo wood	12	/
Farm & Side-line Products Processing	13	13
Food Production	14	14
Beverage Manufacturing	15	15
Tobacco Processing	16	16
Textile Industry	17	17
Clothing, Shoes, Hats Manufacturing	18	18
Leather, Fur, Feathers Manufacturing	19	19
Timber Manufacturing	20	20
Furniture Manufacturing	21	21
Papermaking & Paper Products	22	22
Printing Industry	23	23
Cultural Educational & Sports Goods	24	24
Petroleum Processing & Coking	25	25
Chemical Raw Materials & Chemical Products	26	26
Medical & Pharmaceutical Products	27	27
Chemical Fibre	28	28
Rubber Products	29	29
Plastic Products	30	30
Non-metal Mineral Products	31	31
Ferrous Metal Smelting & Rolling Processing	32	32
Non-Ferrous Metal Smelting & Rolling Processing	33	33
Metal Products	34	34
Ordinary Machinery	35	35
Special Equipment	36	36
Transportation Equipment Manufacturing	37	37
Electric Equipment & Machinery	40	39
Electronic Communication Equipment Manufacturing	41	40
Instrument & Apparatus Manufacturing	42	41
Handicrafts & other Manufacturing	43	42
Waste Material Recycling Processing	/	43
Electricity, Heat Production & Supply	44	44
Gas Production & Supply	45	45
Water Production & Supply	46	46

Appendix D. Variable definition and Classification standards

Patent: the number of a firm's patent applications.

New product output value: output value from a firm's new products.

R&D expenditure: a firm's expenditure on research and development (R&D) investment.

Sales: a firm's total sales including domestic and overseas sales.

Cash flows: a firm's net income plus current depreciation.

New long-term debt issue: a firm's difference between long-term debt in year *t* and *t-1*.

Total assets: the sum of a firm's long-term assets and current assets. Long-term assets comprise fixed assets(tangible assets), intangible assets, deferred assets, long-term investments, and other long-term assets. Current assets include accounts receivable, inventories, short-term investments, and other current assets.

Real total assets: a firm's total assets are deflated using provincial ex-factory producer price indices (PPI) conducted by the NBS of China.

Age: a firm's age is calculated by the difference between its accounting year and the year when it was established.

Political affiliation: an index of firms' political affiliation (lishu) whose categories are – 10, firms are politically affiliated at central level; 20, firms are politically affiliated at the provincial level; 40, firms are politically affiliated at the prefecture-level; 50, firms are politically affiliated at the county-level; 61, 62 and 63, firms are politically affiliated at sub-district, town or township level; 71, 72 and 73, firms are politically affiliated at community or village level; 90, firms have no political affiliation.

State shares: a firm's paid-in capitals controlled by the State.

SA Index: An index of a firm's financial constraints is from Hadlock and Pierce (2010) based on the firm's size and age. The calculation method of the index is $SA = (-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$. At this equation, size is the log of real total assets. Size is replaced with a log of \$4.5 billion when a firm's real total assets are converted into more than \$4.5 billion. Age is replaced with 37 years when the actual value of a firm's age exceeds 37 years. The value of the SA index would increase steadily with more financial constraints.

Table 3.A4

Description of classification standards

Ownership (based on the majority average paid-in capitals)	SOEs	At least 50% of paid-in capitals are state-owned;
	Private firms	At least 50% of paid-in capitals are private (individuals) owned.
Size	Small	If a firm's real sales are in the lower half distribution of real sales of all firms with the same ownership type in the same GB/T Four-digit industry in a given year;
	Large	If a firm's real sales are in the higher half distribution of real sales of all firms with the same ownership type in the same GB/T Four-digit industry in a given year.
Age	Young	If a firm's age is in the lower half distribution of all firms' age with the same ownership type in the same GB/T Four-digit industry in a given year;
	Mature	If a firm's age is in the higher half distribution of all firms' age with the same ownership type in the same GB/T Four-digit industry in a given year.

Political affiliation	No With	If a firm has no political affiliation (lishu = 90); If a firm is affiliated at a level of village, neighbourhood, township, town, sub-district, county, prefecture, province and central government (lishu <90).
State Shares	No Yes	If a firm has no state shares; If a firm has some state shares.
SA	Low High	If a firm's SA index is in the lower half distribution of all firms' SA indexes with the same ownership type in the same GB/T Four-digit industry in a given year; If a firm's SA index is in the lower half distribution of all firms' SA indexes with the same ownership type in the same GB/T Four-digit industry in a given year.

For firms' ownership, all firms are grouped into six categories based on the majority (at least 50%) of registered paid-in capital: state-owned enterprises (SOEs); foreign firms; private firms; collective firms; Hong Kong, Macao or Taiwan (HMT) firms; and mixed ownership firms. Specifically, we regard firms with the majority of state capitals as SOEs; firms with the majority of foreign capitals as foreign firms; firms with the majority of capitals from Hong Kong, Macao and Taiwan as HMT firms; firms with the majority of individual capitals as private firms; firms with the majority of capitals from collective investors as collective firms; firms with the majority of capitals from legal entities and firms without the majority of any type of capitals as mixed-ownership firms. Some papers group firms with the majority of capitals from legal entities into private firms (Ding et al., 2013; Guariglia et al., 2011; Guariglia & Liu, 2014). As one form of registered paid-in capitals, capitals from legal entities are a mixture of capitals from state-owned legal entities and private legal entities. However, the firms that are invested mainly by state-owned legal entities should not be classified as SOEs. In this dataset, we cannot exactly distinguish which firms are invested mainly by state-owned legal entities and which firms are mainly invested by private legal entities since this dataset does not record it. Thus, to alleviate estimation bias, we only group firms with the majority of individual capitals into private firms and firms with the majority of state capitals into SOEs. For firms with the majority of capitals from legal entities, we have to classify them as one form of mixed-ownership firms. We also estimate if firms mainly invested by legal entities as private firms and all results keep consistent. Firms without the majority of any type of capitals is another form of mixed-ownership firms. For example, the firm with the legal person code of '613991812' in 2002 that has 43.7% of state capitals, 42.8% of individual capitals and 13.5% of foreign capitals is one mixed-ownership firm. This form of mixed-ownership firms makes up a small fraction of our sample, just around 1.6%. Since we compare the estimation results between SOEs and private firms in our main analysis, thus we only report the standards of SOEs and private firms in Table 3.A4.

Appendix E. Distribution of the number of prefecture-level administrative divisions for firms' patent applications (detailed explanation of maps of Fig. 3.5 and Fig. 3.6)

Table 3.A5

Distribution of the number of prefecture-level administrative divisions for firms' patent applications

First. Average participation rate of firms' patent applications

Participation rate \ Region	Eastern (Coastal)	Central	Western	Total
(0 – 1.09%]	8	30	48	86
(1.09% - 1.87%]	24	34	27	85
(1.87% - 3.26%]	38	25	21	84
(3.26% - 8.77%]	31	21	34	86
Total	101	110	130	341

Average number of patent applications per 1,000 firms

Number \ Region	Eastern (Coastal)	Central	Western	Total
(0 – 27.67]	9	23	54	86
(27.67 - 62.71]	24	40	20	84
(62.71 - 136.56]	39	24	23	86
(136.56 - 1597.76]	29	23	33	85
Total	101	110	130	341

Appendix F. Overview of subsidy policies for all county-level cities of Suzhou during the period from July 2004 to April 2008

We obtain the data from the study of Lei et al. (2012) and show them in Table 3.A6. We can find that the number of subsidies for all types of patent applications in Zhangjiagang increased after June 2006. Specifically, subsidies for invention patent applications increased from 1,500 to 3,000 + 10,000 (the '+' means the reward for granted invention patent); subsidies for utility model patent applications increased from 1,000 to 1,500; subsidies for design patent applications increased from 500 to 1,000. As a comparison, subsidies for all types of patent applications across the other five neighbouring county-level areas of Suzhou remained unchanged until April 2008 (the subsidy policy in Changshu changed after April 2008). The Suzhou county-level city is the combination of municipal districts of Suzhou prefecture-level city (in China, a municipal district of one prefecture-level administrative division is a county-level administrative division).

Table 3.A6

Amount of subsidies (Unit: Chinese Yuan) for patent applications across county-level cities of Suzhou

	Before June 2006			After June 2006		
County-level city	Invention patents	Utility model patents	Design patents	Invention patents	Utility model patents	Design patents
Zhangjigang	1,500	1,000	500	3,000+10,000	1,500	1,000
Wujiang	2,000	1,000	800		unchanged	
Taicang	4,000+5,000	1,000	1,000		unchanged	
Suzhou (urban districts)	4,000	1,000	1,000		unchanged	
Kunshan	4,000	1,000	500		unchanged	
Changshu	2,000	1,000	1,000		unchanged	

Chapter 4

To what extent does political turnover affect the finance-innovation nexus: Evidence from China

We examine how local policy turnover affects financial development and corporate innovation nexus in China. Using a large panel of 739,672 industrial firms across 305 cities over the period 2003 – 2014, we find that local political uncertainty arising from local policy turnover reduces the positive effect of city-level financial development on corporate innovation while local political turnover alone encourages corporate innovation. Further evidence shows that the moderating effect played by local political turnover on the positive relationship between financial development and innovation varies across turnover types of local government heads, firms' political connections and financial constraints. The results are robust to the use of various estimation methods. Our findings shed light on how both political and financial systems influence corporate innovation in China with a weak institutional environment.

Chapter 4
To what extent does political turnover affect the finance-innovation nexus: Evidence from China

4.1. Introduction

The importance of innovation to economic growth has been widely discussed (Schumpeter, 1911; Solow, 1957; Kogan et al, 2017). Although China has become the second-largest economy during the past few decades with phenomenal economic growth, it now faces pressure due to rising costs of production factors such as labour or capitals.[118] Additionally, under the background of the emerging global trade protectionism and the COVID-19 pandemic recession, China's economy is facing a lot of challenges, such as the steadily slowing growth speed.[119] To maintain high economic growth in the future, China, perhaps, needs to pursue a strategic transformation from investment-driven growth to innovation-driven growth, and innovation is becoming a critical force for China's sustained economic growth. However, because innovation typically demands significant fund, faces high failure probability and has a long-term investment cycle (Holmstrom, 1989), research and development (R&D) investment are likely to be subject to financial constraints. It becomes critical for China to promote a financial system to better serve corporate innovation. Meanwhile, given a unique socialist system, Chinese firms are more likely to exposed to government intervention, political turnover/uncertainty has a substantial impact not just on enterprise investments e.g. innovation

[118] The report issued by the State Information Center (SIC) of China (http://www.sic.gov.cn/News/455/7360.htm) describes the increase in the costs of production factors. For example, China is facing a decrease in its domestic demographic dividend. According to the data in *China Statistical Yearbook* published by the National Burear of Statistics (NBS) of China (http://www.stats.gov.cn/tjsj/ndsj/), the fraction of people aged 65 or above clearly increase from around 7.43% in 1998 to 12.57% in 2019. The fast increase of aging population comes with rising labour costs. The actual growth rate of average salary in China from 2008 to 2014 is 9%, while during the same period the rate is 1.9% in the US, 0.5% in the Europe and -0.8% in Japan.

[119] Since the initiation of economic reforms and open-up in 1978, China's GDP rapidly grew at an average rate exceeding 9% annually until 2017, compared with a growth rate of 2.9% for the global economy (EY, 2018). The China-United States trade war staring from the year 2018 is one of the factors that lead to a decrease in China' GDP growth rates from 6.7% in 2018 to 6.1% in 2019 (according to the World Bank). The COVID-19 pandemic recession makes that China's GDP growth rate sharply dropped to 2.3 in 2020% (according to the NBS of China).

but also on their access to finance (An et al., 2016; Xu et al., 2016; Chen et al., 2020). Thus, in this study, we examine how city-level financial development affect corporation innovation, and further investigate the extent to which policy turnover affects the relationship between innovation and finance and the moderating effects vary across different turnover types, political connections and financial constraints.

Along with the rapid growth of China's economy over the past few decades to the world's second-largest economy, China's innovation capability has also substantially improved. According to the report of 'Global Innovation Index 2020' published by the World Intellectual Property Organization (WIPO), China edged into the top 25 of the innovation ranking in 2016 and moved to the 14th in 2020.[120] Among the 131 economies in 2020, China is the only-middle-income economy in the top 30, even higher than some advanced economies such as Japan (16th), Canada (17th) and Australia (23th). The report also shows that as an emerging market, China is a world leader based on several key output indicators such as the number of patent applications which is one of the widely used metrics for measuring innovative activity. Specifically, the number of international patent applications filed by China via WIPO's Patent Cooperation Treaty (PCT) is 59,193 in 2019, which is the first time that China surpasses the US (57,499).[121] Despite an estimated drop in global GDP of 3.5% in 2020 due to the COVID-19 pandemic recession, China remains the largest user of WIPO's PCT with 68,720 patent filings, representing a 16.1% growth rate from 2019. Additionally, China's R&D spending rose by 8.6% in 2018. China has not experienced aggregate R&D declines since the 2008-2009 financial crisis. In recent years, Chinese governments also have realized the importance of

[120] The report of 'Global Innovation Index 2020' could be browsed through the website address: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2020.pdf.

[121] The data is from the report of 'Innovation Perseveres: International Patent Filings via WIPO Continued to Grow in 2020. Despite COVID-19 Pandemic' published by the WIPO in March 2021. The report could be viewed via: https://www.wipo.int/pressroom/en/articles/2021/article_0002.html.

indigenous innovation and adopted some policies to tackle the problem of overwhelming dependence on foreign technology. For example, in May 2015, the Chinese premier Li Keqiang released the plan of 'Made in China 2025', which aims to promote indigenous innovation to help China to shift from being the 'Made in China' (producing cheap and low-quality goods) to the 'Made with Wisdom in China' (producing higher-value goods and services).

As the largest emerging market and manufacturing economy in the world, China's financial system has developed dramatically with its rapid economic growth during the last decades. Before 1984, China did not have an integrated financial system. Since 1984 when the four state-owned banks (the 'Big-Four') took over the commercial banking business from the central government of China, China has experienced a rapid expansion of financial intermediation over the past decades.[122] Specifically, compared to the excessive growth speed of China's gross domestic product (GDP) from 727.85 billion Chinese Yuan (CNY) in 1984 to 99.09 trillion CNY in 2019, the amount of total loans in China's financial institutions even shows a greater upward tendency from 441.96 billion CNY in 1984 to 153.11 trillion CNY in 2019.[123] Thus, the ratio of China's total loans to GDP has increased from 60.72% in 1984 to 154.52% in 2019. Although Schumpeter (1911) finds that financial development is critical for a nation's innovation, prior research has not found consistent evidence that financial development contributes to China's rapid economic growth (Allen et al., 2005). Little is known about the link between financial development and corporate innovation in China.

As the largest communist country in the world, China's political and economic systems are significantly different from those of western countries. Despite China's claim that it has gradually shifted from a planned economic system to a market-oriented system since the reform

[122] The 'Big-Four' commercial banks in China are Bank of China Limited, Agricultural Bank of China Limited, Industrial and Commercial Bank of China Limited and China Construction Bank Corporation.

[123] The data is from the *China Statistical Yearbook* 2020 (http://www.stats.gov.cn/tjsj/ndsj/).

and opening up in 1978, the Communist Party of China (CPC) has absolute authority in every aspect of local political and economic systems. Thus, political factors still play an important role in China's economy. For example, in China, the government dominates the economy. Local government officials could have a great influence on the allocation of capitals in the economy (Jiang et al., 2020). A change in the local political environment e.g. political turnovers of local government heads could thus have a significant impact on firms' activities through policies such as access to debt financing, land use, business permit and government subsidies. It is likely that firms' innovation activities as a key strategical investment are also affected by political turnovers of local government officials. Most of the previous studies of the impact of political uncertainty on innovation focus on cross-country data or developed economies (Bhattacharya et al., 2017; Pertuze et al., 2019; Ovtchinnikov et al., 2020), and very few papers have examined the impact of local political uncertainty such as political turnovers on corporate innovation in China. Thus, in this study, we explore the extent to which local political turnover affect firms' innovation activities. We particularly focus on whether political turnover has an impact on the relationship between finance and innovation in China.

To empirically evaluate the impact of city-level financial development and local political turnover on firms' innovation activities in China, we use a large unbalanced panel data set of 3,160,672 observations covering 739,672 industrial firms in 305 cities over the period from 2003 to 2014. We focus on financial development and political turnover at the prefecture-level (cities) instead of the province-level or county-level for the following reasons. On the one hand, the prefecture-level government plays a major role in economic plans since it can directly control state-owned enterprises (SOEs) and indirectly affect private sectors through regulation, license and network (Piotroski & Zhang, 2014). On the other hand, the data at the prefecture-level is more advantageous than the ones at the provincial-level as the former provides more information and variations in local financial development and political turnovers.[124]

We find that both city-level financial development and local political turnovers promote firms' innovation activities. However, we find that local political uncertainty arising from local political turnovers attenuates the positive effect of financial development on innovation. The results remain consistent with those of various robustness tests. Specifically, to eliminate the endogeneity issues, first, we use the fraction of seniors as the instrumental variable for the financial development variable and an indicator of predicted political turnovers as the instrumental variable for the political turnover variable to confirm the causality; second, we employ alternative measures of financial development, political turnover and innovation to mitigate measurement errors; third, we cover the contemporaneous terms of independent variables taking potential omitted variables into account; finally, we make more additional robustness tests including change of 'above-scale' sample, deletion of municipalities and other estimation methods.

In addition to robustness tests, we make a further extension to find that the moderating effect of political turnover on the positive relationship between financial development and corporate innovation varies across turnover types of local government heads, firms' political connections and financial constraints. Specifically, the moderating effect of political turnover is more pronounced for firms facing abnormal political turnovers, firms with political connections, and firms with less financial constraints.

The paper has contributions as follows. Firstly, it contributes to the literature on finance and innovation. Our paper is distinct from but also complementary to the previous studies of

---

[124] There are 31 provincial administrative regions in mainland China while about 300 prefecture-level cities. Thus, compared to the data at the provincial-level, the data at the prefecture-level is more plentiful.

financial development and innovation. Previous studies on the effect of financial development on innovation mainly focus on cross-country data or developed economies (Xiao & Zhao, 2012; Hsu et al., 2014; Ang & Kumar, 2014; Zhu et al., 2020). Unlike earlier studies, we are the first to use a rich set of cross-city data together with a large census dataset of firms including unlisted and listed firms to examine specific economic mechanisms through which financial development affects corporate innovation in China. Unlike listed firms which can raise external funds from the equity market, unlisted firms obtain external funds only from the credit market. Thus, unlisted firms can better capture the effect of the local credit markets in more than 300 cities on corporate innovation in China than listed firms which are mainly distributed in specific cities. [125] Additionally, compared to most of the previous papers on China's financial development based on national or provincial data (Liang & Teng, 2006; Zhang et al., 2015; He et al., 2017), we choose the financial development data across cities, which can better explore local financial development in depth.

Secondly, our paper contributes to the literature on the effect of political uncertainty/ turnover on innovation. Some studies have explored the impact of political uncertainty on innovation based on cross-country data or western countries (Bhattacharya et al., 2017; Pertuze et al., 2019; Ovtchinnikov et al., 2020), while the related studies in China are still sparse. As the largest communist country with a unique political system, China provides an opportunity for us to investigate the effect of local political uncertainty on corporate innovation. The investigation helps us to understand the unique political mechanism through which how corporate innovation is affected. As the same as the aforementioned contribution, we link the

[125] The distribution of listed firms in China is extremely unbalanced. Most listed firms are located in 4 municipalities, sub-provincial cities or capital cities of provinces. The majority of prefecture-level cities own a small number of listed firms, or even zero. Thus, compared to listed firms, unlisted firms which are naturally distributed in all cities can better reflect the effect of financial development across cities.

data of unlisted firms with the data of political turnovers at the city-level, which is complementary to the previous studies on political uncertainty and innovation.

Thirdly, our paper contributes to the literature on corporate innovation in China. Prior studies have explored the factors related to innovation in China, such as financial constraints (Guariglia & Liu, 2014), intellectual property rights protections (Fang, et al., 2017) and input tariff liberalization (Liu & Qiu, 2016). However, studies that have tested the effects of financial development and political turnovers on corporate innovation in China are not systematically consolidated.

Fourth, our paper contributes to the literature on innovation by providing new insights into the real effects of financial development related to political turnover. In the Chinese context, we are the first to enrich the emerging research by examining the financial channel, e.g., financial development, through which political uncertainty/turnover affects corporate innovation. Considering that the unique government-intervention system is inextricably linked to every aspect of social life in China, China's financial system is significantly affected by changes in the political environment. Thus, the study about the role played by political turnover in the relationship between financial development and corporate innovation can improve our understanding of China's marvellous economic performance over the past few decades.

The rest of the paper is organized as follows. In Section 4.2 we introduce the background of China's innovation, financial system and political system. In Section 4.3 we develop our testable hypotheses. In Section 4.4 and Section 4.5, we describe the variable measures and the datasets used in the study. In Section 4.6, we present our model specifications and summarize the variables in models. In Section 4.7, we show our empirical results. In Section 4.8 we make robustness tests and in Section 4.9 we make further tests to other factors.

Finally, we conclude this paper in Section 4.10 and provide detailed information on some related aspects in the appendices.

4.2. Background of China's innovation, financial system and political system

4.2.1. China's innovation

China's economic boom has coincided with a transformation from a laggard to a leader in innovation. Besides the enormous strides in the global innovation ranking, China has also experienced substantial growth in patent applications, which is a poster child of innovation. Specifically, since the year 1985 when the patent system was established in China, China surpassed the US in 2011 and has become the country receiving the most number of patent applications.[126] According to the report of 'World Intellectual Property Indicators 2018' released by the WIPO, the number of patent applications filed by China to the WIPO rose from 18,700 in 1995 to 1,381,594 in 2017, with an average annual growth rate of 23%.[127] According to the *China Statistical Yearbook* published by the NBS of China, the number of domestic patent applications to the State Intellectual Property Office (SIPO) increased from 13,680 in 1986 to 4,195,104 in 2019.[128] Additionally, China's R&D spending has soared in the past thirty years. According to the statistics of the Organisation for Economic Co-operation and

---

[126] *The Economist*, 'How innovation is China? Valuing patents', Jan. 5th, 2013. https://www.economist.com/business/2013/01/05/valuing-patents.

[127] The report of 'World Intellectual Property Indicators 2018' can be viewed via: https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2018.pdf.

[128] The *China Statistical Yearbook* could be viewed via: http://www.stats.gov.cn/tjsj/ndsj/. Actually, the year when the patent system was established in China is 1985. However, the number of patent applications is recorded from 1st April 1985. This is the reason why I choose the year 1986 as the starting year of recording the number of patent applications.

Development (OECD), China's gross domestic spending on R&D rose from $13,119 million in 1991 to $462,578 million in 2018, which is only behind the US ($551,518 million).

Although China's innovation nationwide has made significant progress over the past decades, there are still some disadvantages. The biggest challenge is unbalanced regional development. Compared to central, western and northeast regions, coastal (eastern) regions are the main areas where innovation activities take place in China. Specifically, according to the *China Science and Technology Statistical Yearbook*, the intramural expenditure on R&D of provinces in coastal regions exceeds 146.14 million CNY, accounting for 66.00% of the national total (about 221.44 million CNY).[129] The provinces that have the highest R&D spending are Guangdong (30.98 million CNY), Jiangsu (27.80 million CNY), Beijing (22.34 million CNY), Zhejiang (16.70 million CNY) and Shanghai (15.25 million CNY), all in coastal regions. The five provinces with the highest number of domestic patent applications are also located in coastal regions: Guangdong (807,700), Jiangsu (594,249), Zhejiang (435,883), Shandong (263,211) and Beijing (226,113). The unbalanced regional development of innovation is largely determined by the unbalanced development of China's economy. Due to the significant fund demand for R&D projects, only firms with good access to finance could invest in R&D activities and most of these firms tend to be located in coastal regions. Therefore, China's innovation t heavily rely on government supports and funding. For example, in 2019 about 76.3% of China's R&D funding is supported by governments and only 20.5% is financed by enterprises. In contrast in most of the developed countries, the proportion of R&D funding supported by governments is only about 30% and the proportion financed by enterprises

[129] The *China Science and Technology Statistical Yearbook* could be viewed via: http://www.stats.gov.cn/ztjc/ztsj/kjndsj/.

exceeds 50%.In 2019 only about 11.7% of R&D researches in China is applied research while the corresponding figure for the developed countries usually exceeds 30%.

4.2.2. China's financial system

Over the past 40 years, China has been experiencing very rapid financial development. Before the 1980s, there was no commercial bank in China. As the sole bank and the central bank in China, the People's Bank of China (POBC) was responsible for all banking transactions in China. China's reform on its financial system took place in the year 1984 when the 'Big-Four' state-owned banks (SOBs) took over commercial banking business from the POBC and the POBC only functioned as the central bank. After that, there is an expansion of banking financial institutions and non-banking financial institutions. However, the financial system in China has been dominated by state-controlled banks, e.g. the 'Big-Four' banks, which has resulted in poor lending decisions made for SOEs and a misallocation of financial resources.

Since 1994 China's central government has carried out a series of financial reforms to make banking organizations less administrative and more independent. For example, three policy banks were established in 1994 and the Commercial Bank Law was promulgated in 1995.[130] Meanwhile, more and more types of banks have been established since 1994. For example, the China Minsheng Bank Corporation (CMBC), the first privately-owned bank in China, was established in 1996. Some urban commercial banks have taken the form of joint-equity and conduct business in the cities where they are located. As the number of joint-equity commercial banks has gradually increased, the market share of the 'Big-Four' has declined but still dominated in China's financial market. Additionally, as more firms have the motivation to go public, the central government also established two stock exchanges, the Shanghai Stock

[130] The three banks are China Development Bank, Export-Import Bank of China and Agricultural Development Bank of China.

Exchange in 1990 and the Shenzhen Stock Exchange in 1991 to construct the equity market in China.

At the end of 2001, China formally joined the World Trade Organization (WTO). To meet the WTO requirement of financial liberalization, China's central government has adopted more policies. For example, more freedom is allowed to give to the capitals from foreign banks. In 1996, the Asian Development Bank (ADB) bought a stake of about 1.9% share from the China Everbright Bank, which is the first time that a foreign bank invests in a domestic bank in China. The China Banking Regulatory Commission（CBRC）also issued policies in 2003 to promote the shareholdings of foreign banks. Since 2001, the central government gradually eased the geographical and client restrictions on Renminbi (RMB) businesses conducted by foreign banks. Specifically, in 2001 only 4 cities (Shenzhen, Shanghai, Tianjin and Dalian) were allowed to open up to foreign banks, while in 2006 foreign banks were allowed to set up branches and conduct RMB business in all cities. At the end of 2006, 312 foreign banks had set up branches and carried out RMB business in China, and the total assets of financial institutions controlled by foreign banks account for 2.11% of the total assets of China's entire financial institutions.

4.2.3. China's political system

With the economic reform starting from 1978, China also has gradually reformed its political system, such as the set-up of the 'tenure system for leading cadres'. Before the 1980s, the 'life tenure for leaders' system was dominating in China. For example, Mao Zedong was the supreme leader of China from the year 1949 when the People's Republic of China was founded until the year 1976 when he passed away. Starting from the speech in 1980 of Deng Xiaoping who is the pioneer of the reform and open up, China steadily abolished its system of 'life tenure for leaders'. In 1982, the fifth National People's Congress incorporated the 'tenure system for leading cadres' for national leaders into the Chinese Constitution, which states that national leaders have a tenure period of five years and serve no more than two consecutive terms. Following the central government, local governments at all levels have gradually established the 'tenure system for leading cadres'. Although the Chinese Constitution does not set term limits for cadres of the CPC (the sole ruling party in China), the document issued by the CPC Central Committee in 2006 claimed that CPC cadres at all levels of government typically serve the same five-year term as government officials.[131]

Although China has gradually reformed its political system, it is still distinct from western countries. Unlike most western countries whose government top leaders can come from various political parties and are decided by votes, China is directly controlled by the CPC at all levels of government. Thus, the top leader of the Chinese government at all levels must be a member of the CPC, who is called the secretary of the party committee (hereafter referred to as party secretary), and all local government officials must follow the leadership of the local party secretary. Additionally, higher party organizations delegate power to subordinate party organizations, which causes local party secretaries to hold the supreme power of decision-making and allocation of resources. Owing to the Chinese government's unique promotion system, which is positively related to local GDP growth during their terms[132], local party secretaries have incentives to use political tools to promote the local economic growth. Although CPC cadres typically have a five-year tenure in line with a party congress held every five years, the CPC has absolute authority to changes the local party secretary in a given region to achieve specific economic goals.[133] However, the change in political leadership is likely to

[131] The link of the document in Chinese version: http://cpc.people.com.cn/GB/64093/64387/4671315.html.

[132] Maskin et al. (2000) suggest that promotion is one of the most important career ambitions of a politician in China.

[133] It is also a common phenomenon that many local party secretaries serve less than five-year in office.

have a dramatic impact on firms' business activities as firms become uncertain about future policies. Besides, some local party secretaries are removed from office or resign voluntarily due to particular political reasons e.g. corruption or public unrests. For example, due to the delay in reporting the COVID-19 outbreak that happened in Wuhan (the capital city of Hubei Province) in December 2019, the party secretary of Hubei Province (Jiang Chaoliang) and the party secretary of Wuhan City (Ma Guoqiang) resigned from their posts in February 2020. These unexpected turnovers of local party secretaries could create significant political uncertainty for the enterprises in local areas.

4.3. Hypothesis development

In this section, we develop three testable hypotheses by discussing previous literature and economic theories. First, we test whether city-level financial development encourages firms' innovation activities in China. Second, we examine whether local political turnover promotes firms' innovation activities in China. Third, we test the moderating effect played by local political turnover on the relationship between financial development and corporate innovation.

4.3.1. Financial development and corporate innovation

Since the innovation process is long-term, idiosyncratic and unpredictable (Holmstrom, 1989), firms are likely to prefer to invest in short-term projects than R&D projects. Even firms that have strong incentives to innovate may face a problem of financial constraints due to the large fund demand of R&D. Thus, firms' innovation activities are not only limited by internal finance but also have to rely on external finance (Ayyagari et al., 2011). However, the information asymmetry between banks and firms leads to high costs of external financing, since some firms are reluctant to completely expose their potential R&D projects to market and thus banks cannot fully understand the R&D projects (Aboody & Lev, 2000; Anton & Yao, 2002). Financial markets significantly affect firms' decisions on how to finance their activities since a developed financial system can efficiently mobilize financial savings and allocate financial resources (Greenwood & Jovanovic, 1990; Levine, 1991; Saint-Paul, 1992; Fisman & Love, 2004). Thus, a higher financial development can overcome problems of moral hazard and adverse selection and thus reduce firms' costs of external finance, which makes it easier for firms to finance their activities using bank loans or other forms of external finance (Rajan & Zingales, 1998; Love, 2003; Fisman & Love, 2003; Ge & Qiu, 2007). With an increasing number of financial institutions that have emerged in each city in China over the past decades, China's financial market has been a tremendous development. A higher level of financial markets can provide more external financing sources to firms and reduce costs of firms' external finance. Firms in cities with a higher level of financial development are more likely to obtain external funds to achieve the fund demand of R&D projects. Based on the above conjectures, therefore, we hypothesize as follows:

Hypothesis 1: *City-level financial development encourages corporate innovation in China.*

4.3.2. Political turnover and corporate innovation

In China, local officials with high political ranking can have huge benefits, such as privilege and social status. One of the local government officials' goals in China is political promotion when they finish their terms. The final promotion decisions of local officials are usually made in the last year or the penultimate year of their terms, so the local GDP growth in the early years of their terms is heavily weighted (Ru, 2018). Thus, new appointed local government leaders tend to instantly use more policy tools such as tax reduction or patent subsidies to encourage corporate innovation to boost the local economy. Local political turnover could stimulate local corporate innovation. This is also the interpretation that a lot of firms may not apply for patents even they have potential innovation outputs. Because the value of innovation investments may increase as political turnovers also create innovation opportunities in China's particular political turnover system, firms would wait for the perfect time such as political turnovers to maximize their benefits from innovative products. Due to the unique political turnover system and the local government officials' promotion ambitions in China, we propose our second hypothesis as follows:

Hypothesis 2: *Local political turnover promotes corporate innovation in China.*

4.3.3. Financial development, political turnover and corporate innovation

Political turnovers of local government leaders could potentially lead to political uncertainty, which may attenuate the positive effect of financial development on innovation activities. First, in areas with political uncertainty, information asymmetry between external investors and firms is higher, which in turn imposes additional costs on the debt and loan contracts from banks (Francis et al., 2014; Nagar et al., 2019). Second, some previous studies have found the effect of political uncertainty on default risk, which could increase the premium of external funds (Campbell et al., 2001; Mei & Guo, 2004; Bloom et al., 2007; Vavra, 2014). Third, banks may intentionally reduce external funds to firms due to China's unique government-intervention model. In China, most loans are still controlled by state banks such as the 'Big-Four', which are closely connected to their local governments. With a change in the local political environment, banks may ration credit to avoid potential political risks. Given the fact innovation investment is highly dependent on external finance, firms' innovation activities are highly affected by credit rationing. Fourth, the risk of expropriation by the government could be higher during the period of political uncertainty, innovative firms might perceive the risk and invest less in R&D projects even they have access to finance. Therefore, the relationship between financial development and innovation could be attenuated due to political uncertainty. Therefore, we put forward our third hypothesis as follows:

Hypothesis 3: *Political uncertainty arising from local political turnovers reduces the positive effect of city-level financial development on corporate innovation.*

4.4. Variable measures

In this section, we introduce the measures of firms' innovation activities, city-level financial development and local political turnover. Appendix D shows detailed information on variable definitions.

4.4.1. Measure of innovation

In the study, we use the number of patent applications submitted by a firm in a given year to measure firm-level innovation output. Many papers have used patents to measure firm-level innovation (Liu & Qiu, 2016; Acharya & Xu, 2017; Fang et al., 2017). Using patents to measure innovation output has advantages (Bronzini & Piselli, 2016). Specifically, patents can better reflect firm-level innovative performance (Hagedoorn & Cloodt, 2003) because the patent application and grant require more stringent processes governed by government and specific experts. Griliches (1990) also suggests that patent activity can be a good measure of invention activity since patent activities are regarded as a growth indicator of economically valuable knowledge.

Specifically, we construct a proxy, $Pat_{i,t}$, which represents the number of all three types of patent applications for a firm i in a given year t. However, the majority of firms in the sample do not have patent applications, which means the value of $Pat_{i,t}$ for most observations equals 0. Specifically, approximately 93.81% of sample observations have no patent applications while the largest value of $Pat_{i,t}$ is 31,805. To avoid the problems of too many zero values and the big dispersion in $Pat_{i,t}$, we construct a new proxy, $Log\ (Pat_{i,t} + 1)$, by using the natural logarithm of $Pat_{i,t}$. The explanation that we employ the number of patent applications instead of patents granted is application years can better reflect the actual time of innovation (Griliches et al., 1986). We use the number of patents granted as a robustness check.

Besides patents, some papers use new product output value and R&D expenditure as alternative measures of firms' innovation activities (Hagedoorn & Cloodt, 2003; Guariglia & Liu, 2014; Zhu et al., 2020). However, because the data of new product output value and R&D expenditure are incompletely recorded in the NBS firm-level dataset during the sample period, we do not choose them.[134]

4.4.2. Measure of financial development

To examine the extent to which financial development affects firms' innovation activities in China, we construct a set of financial indicators to measure financial development. We measure financial development at the city-level, which should reflect the overall depth and size of financial intermediations across cities.[135]

Previous papers have employed some indicators of financial development across countries. For example, Rajan and Zingales (1998) use the ratio of stock market capitalization plus domestic credit to GDP in one country to measure the country's overall financial development. Levine et al. (2000) measure financial development by using the values of credits

[134] Specifically, the data of new product output value and R&D expenditure in the NBS firm-level dataset are only recorded from 2003 to 2007 and missing in 2004, while our sample covers the period from 2003 to 2014. Thus, new product output value and R&D expenditure are not good proxies of firm's innovation activities in the study.

[135] Appendix B shows the detailed information on the cities used in the study.

provided by financial intermediaries to the private sector divided by GDP. In the study, we construct a variable, $FinDev_{i,c,t}$, to measure the financial development level of city c where a firm i is located in year t. Specifically, following Zhang et al. (2012) we use a set of indicators to measure financial development. The first is the *credit ratio* which is the ratio of overall loans in the city c's financial system (including banking institutions and non-banking financial institutions) to the city c's gross regional product (GRP) in year t. The *credit ratio* measures the overall depth of the city's financial intermediaries. The second is the *deposit ratio* which is the ratio of overall deposits in the city c's financial system to the city c's GRP in year t. The *deposit ratio* measures the overall size of financial intermediations. The third is the *saving ratio* which is the ratio of overall household savings in the city c's financial system to the city c's GRP in year t. The *saving ratio* measures financial development in terms of mobilizing household savings.

4.4.3. Measure of political turnover

Following An et al. (2016), Xu et al. (2016), Amore and Minichilli (2018), we use political turnovers of city government leaders, which also can capture local political uncertainty. Because the CPC is the sole ruling party in China, the city government leader in China is the city party secretary instead of the mayor who serves as vice city party secretary. The city party secretary has absolute authority in decision-making, no matter at which city level. When the current city party secretary is replaced, there is political uncertainty in the short run. Thus, we construct a dummy variable, $PT_{i,c,t}$, to indicate local political turnover, which takes a value of one when the city c where a firm i is located experiences an official turnover of city party secretary in year t and zero otherwise. Additionally, since many official changes happen in the second half of the year, if we used a calendar year (from 1st January to 31st December) to capture the occurrence time of turnovers, an estimation error of political uncertainty potentially exists. Thus, following An et a., (2016), Xu et al., (2016) and Chen et al., (2020), we adjust the variable $PT_{i,c,t}$ according to the exact dates of leaving office and taking office for each city party secretary. Specifically, if a political turnover of one city party secretary occurs in the first half (from 1st January to 30th June) of year t, we treat it as happening in year t; if a city party secretary change occurs in the second half (from 1st July to 31st December) of year t, we treat it as happening in next year $t + 1$. For example, Wang Yang, Bo Xilai and Zhang Dejiang are the former city party secretaries of Chongqing (one of four municipalities). Wang left office and Bo took office in November 2007. Bo left office and Zhang took office in March 2012. Hence, we define the years 2008 and 2012 as the turnover years. Additionally, using exact dates could capture two changes of city party secretary in one calendar year for a small number of cities, while using calendar years would omit one change. For example, Xi Jinping was inaugurated as the city party secretary of Shanghai (one of four municipalities) in March 2007 but was promoted to the central government in October 2007. If we use calendar years to capture the political turnovers, the value of $PT_{i,c,t}$ equals 1 only for the year 2007 but 0 for the year 2008. Thus, using exact dates instead of calendars years is a better measure. The occurrence of political turnover ($PT_{i,c,t} = 1$) can reflect a spike of local political uncertainty.

4.5. Data

The paper uses consolidated data that includes information on firm-level financial variables from the NBS of China, firm-level patents from the CNRDS, city-level financial development from the *China City Statistical Yearbook*, and city-level political turnovers collected manually from the websites. In this section, we introduce the datasets used in the study.

4.5.1. NBS firm-level data

The first data for firm-level financial variables is from the China Annual Survey of industrial firms. Because the data is drawn from the annual accounting reports conducted by the NBS of China, the dataset is called the NBS firm-level data. The dataset can be briefly described as follows: First, the census firm-level dataset is the unique comprehensive coverage of rich information on all 'above-scale' enterprises, such as official names, industry classifications, years of founding and addresses.[136] The dataset also records most items of each firms' operation and financial performance, including the number of employees, total industrial output value, total asset, accumulated depreciation, main business income, etc. Second, the dataset is the largest longitudinal micro-level data available in China, especially for unlisted firms. In the dataset, 95% of the firms are unlisted firms and all firms are distributed in the whole 31 provincial administrative divisions (22 provinces, 4 provincial-level municipalities and 5 autonomous regions) and across all 39 sectors of mining, manufacturing, and public utility.[137] The dataset has a unique legal identifier as the legal person code (*fa ren dai ma*) to each firm (Chang & Wu, 2014), which allows researchers to make a panel data by linking together the observations in years. Third, the big sample of the dataset accounts for the vast majority of China's total industrial output (approximately 90%),[138] which can eliminate

[136] According to the NBS of China, from 1998 to 2006 the 'above-scale' enterprises are all state-owned industrial enterprises and non-state-owned industrial enterprises with annual main business income (i.e., sales) above five million CNY. In 2007, the NBS of China revised the standard of 'above-scale' enterprises to only industrial enterprises with annual sales above five million CNY. In January 2011, the NBS raised the threshold for inclusion of the 'above-scale' enterprises from five million CNY to twenty million CNY of annual sales.

[137] We cannot distinguish the public listed firms from the NBS dataset as there is not an identifier for listed firms in the dataset. Additionally, the dataset does not report the information of firms in Hong Kong, Macao and Taiwan.

[138] For example, according to the national economic census annual report in the year 2004 (http://www.gov.cn/gongbao/content/2006/content_180438.htm), the sales of all industrial enterprises in China in that year is 2.184 trillion. As a comparison, in the database the sales of all sample enterprises in the dataset in 2004 is 1.956 trillion yuan, accounting for approximately 89.5% of the national total.

aggregation problems (Guariglia & Liu, 2014). Firms' heterogeneity also can be taken into account (Bond & Van Reenen, 2007). Thus, the dataset can be a good representative of the broad Chinese industrial economy and many studies have used it in areas of economics and finance, such as economic development (Song et al., 2011), total factor productivity (Hsieh & Klenow, 2009), innovation (Hu & Jefferson, 2009; Liu & Qiu, 2016), and financial constraints (Guariglia et al., 2011; Ding et al., 2013), etc.

In the study, we choose the NBS data from 2003 to 2014.[139] To check the data reliability, we compare the number of firms each year in the dataset with those reported in the *China Statistical Yearbook* conducted by the NBS. Before matching with the patent data and the city-level data, we clean the original data by following some steps. Appendix A shows the detailed information on the comparison and the data cleaning process.

4.5.2. Patent data

The second data for the firm-level patent is from the Chinese Research Data Services (CNRDS) (https://www.cnrds.com/Home/Index#/). The dataset is a comprehensive dataset of China's economy, finance and business. As a comprehensive coverage of patent information in China, the information dataset can be used to explore China's innovation. The dataset records the patent information of unlisted firms since the year 1985, covering the names of the applicant firms and the application years. The most important variable in the dataset is the number of each firm's all types of patent applications (including invention, utility model and design), which can be used to measure firms' innovation output in the study.[140] Since about 95%

[139] The NBS firm-level data is recorded from the year 1996 and now the dataset has been updated officially to 2014. In the study we choose the data starting from 2003 to keep consistent with the data of city-level financial development in China which is recorded from the year 2003.

[140] The three types of patents are different in protection periods, approval requirements and applicable targets.

of observations in the NBS firm-level dataset are unlisted firms, we can merge the information on the number of each firm's patent applications from the CNRDS with the NBS firm-level data through firms' official names.

4.5.3. Financial development data

The third data for city-level financial development is from the *China City Statistical Yearbook* maintained by the NBS of China. The yearbook is a comprehensive dataset that records detailed information on the social and economic development of each city (including municipalities, prefecture-level cities, and county-level cities). By the end of 2014, there are 333 prefecture-level administrative divisions in China and 288 of them are prefecture-level cities.[141] Thus, the *China City Statistical Yearbook* is suitable for researchers to explore the effect of local factors on enterprises' economic behaviours in the area of the whole nation. The data of city-level loans, deposits, and household savings in the yearbook are used to measure financial development, which starts from the year 2003. The yearbook provides two kinds of statistical data: the first is collected from the whole administrative areas of cities (urban and rural regions) and the second is collected from the urban areas of cities. We choose the first kind of data, considering that economic activity may take place in any area of one city. Last, we collect a panel of 306 cities (including 4 municipalities, 287 prefecture-level cities, and 15 county-level cities directly governed by provincial governments) from the year 2003 to 2014 in China.[142] In the rest of the paper, a 'city' refers to a municipality, a prefecture-level city, or

---

[141] The data is from the *China Statistical Yearbook 2015* (http://www.stats.gov.cn/tjsj/ndsj/2015/indexch.htm). Except for prefecture-level cities the other 45 prefecture-level administrative divisions are prefecture-level areas, autonomous prefectures or leagues.

[142] Only a very few number of county-level cities are independently organized outside prefecture-level administrative divisions and directly governed by provincial governments. Thus, we use the data of these county-level cities (available from the year 2011) to link with the firm-level data. During the sample period from 2003 to 2014, one prefecture-level city (Wuhu in Anhui Province) is merged by other prefecture-level cities, so the number

a county-level city directly governed by its provincial government. Appendix B shows detailed information on these cities.

4.5.4. Political turnover data

The fourth data used in this study is about local political turnovers. We manually collect the data of each city party secretary over the period from 2003 to 2014 from the Peoples Network (http://www.people.com.cn/) and the Xinhua Network (http://www.xinhuanet.com/) which are official websites organized by the Chinese central government. We cross-check the collected data with the Baidu Wikipedia (http://baike.baidu.com) which is the most popular search engine in China and Zecheng database (https://www.hotelaah.com/) to ensure the data quality. The data contains the detailed demographics of 1,359 party secretaries in 365 local administrative divisions, including name, gender, age, education etc. We also collect the exact years and months of leaving office and taking office for each city party secretary, which is used to construct the indicator of local political turnover. Appendix C shows the detailed distribution of political turnovers of city party secretary by provincial administrative regions and years.

4.5.5. Merging datasets

We first link the NBS firm-level data with the CNRDS patent data through firms' official names recorded in the datasets. After that, we obtain the information on the number of each firm's patent applications in the NBS firm-level data. Second, we merge the adjusted NBS firm-level data with the city-level financial development data and the political turnover data through administrative codes of cities. Third, we drop the firm-level observations which are

of prefecture-level cities in Anhui Province is decreased from 17 in 2010 to 16 in 2011. Thus, at the end of 2014 there are totally 305 cities in China while we collect the data of 306 cities.

not in the 306 cities collected from the *City Statistical Yearbook*.[143] Combining and adjusting these datasets, we finally obtain a large sample which consists of 3,160,672 observations covering 739,672 firms across 305 cities from 2003 to 2014.[144] All firm-level financial variables are deflated using provincial ex-factory producer price indices (PPI) conducted by the NBS of China.[145]

Table 4.1 shows the distribution of the sample observations in years from 2003 to 2011. The number of firms is the least (168,858) in 2003 and the most (397,721) in 2008 since a national Census on industrial firms happened in 2008. The number of firms decreases from 311,945 in 2009 to 297,670 in 2011 since the threshold for inclusion of the 'above-scale' enterprises is increased from five million CNY to twenty million CNY in 2011. We find that only about 6.19% of observations have patent applications during the sample period, reflecting a low enthusiasm in applying for patents in China. However, the participation rate of patent applications grows steadily from 2.37% in 2003 to 15.00% in 2014, showing that Chinese firms' enthusiasm in applying for patents is increasing. Innovation policies of China's governments may account for the increasing enthusiasm for patent applications. The number of cities in the sample increases from 284 in 2003 to 304 in 2014 since some prefecture-level administrative divisions are adjusted to prefecture-level cities during the sample period.[146] Additionally, from

[143] Some administrative areas where these observations are located are not cities, so they do not have the information on city-level financial development. The number of these observations is 54,806, only around 1.704% of all observations in the NBS firm-level data, also showing that cities are the core components for enterprise activities in China.

[144] In Section 5.3, we collect city-level financial development of 306 cities. One county-level city in Hainan Province does not have 'above-scale' enterprise during the sample period, so final sample observations are distributed in 305 cities.

[145] The provincial ex-factory PPI data could be searched on: http://data.stats.gov.cn/.

[146] For example, Bijie City in Guizhou Province is a prefecture-level administrative area before 2011, which is called 'Bijie Prefecture'. In 2011 Bijie is adjusted from a prefecture-level administrative area to a prefecture-level city, so the *China City Statistical Yearbook* starts to record the information on Bijie City. For the number of cities

the year 2011, the *China City Statistical Yearbook* starts to record information on county-level cities directly governed by provincial-level governments, so the number of cities increases from 286 in 2010 to 302 in 2011.[147] For weighted average city-level FD, although the three ratios of FD initially decrease before the financial crisis starting from the year 2007, they gradually recover after the year 2008.[148] The sharp rise from the year 2008 to 2010 may be stimulated by the '4-Trillion-Yuan Stimulus Package' proposed by the central government.[149] Fig. 4.1 presents the trend line of FD level as described above. Fig. 4.2 and Fig. 4.3 are maps that show the FD level measured as *credit ratio* across cities in 2003 and 2014. The figures show that the FD level is highly unbalanced in cities. 4 municipalities, 15 sub-provincial cities, capital cities of provinces and some coastal cities have a higher FD level compared to the rest.

[*Insert Table 4.1 here*]

[*Insert Fig. 4.1 here*]

[*Insert Fig. 4.2 here*]

[*Insert Fig. 4.3 here*]

The total ratio of political turnover is 25.97% during the sample period 2003 to 2014. The set of peaks are years 2003, 2008, and 2013 which are the three years following the National Congress of the CPC. The National Congress is held every five years in China (in

---

in 2010, we use the data in 2009 and 2011 to capture it. If one firm is recorded in both 2009 and 2011, we cover the city where the firm is located for 2010.

[147] The data of Lhasa City in 2010 is not recorded in the *China City Statistical Yearbook* so Lhasa City is not included in the sample in 2010. This is the reason that the number of cities in the sample decreases from 287 in 2009 to 286 in 2010.

[148] The weight is the number of firms in cities divided by the number of firms nationwide in the sample. We choose to report the weighted average FD level in consideration of city size. Since we cannot calculate the weight in 2010, we replace the weight in 2010 by using the weight calculated in 2009.

[149] The detailed information on the investment plan: http://www.chinadaily.com.cn/business/stimulus_page.html.

2002, 2007, and 2012) and around the Congress, there is a large probability of political turnover for local governments. This is the explanation that many political turnovers of city party sectary occur in the second half of the years 2002, 2007, and 2012, or the first half of the years 2003, 2008, and 2013. For example, the two turnovers of city party secretary of Beijing in the first ten years of the 21st century occur in October 2002 and July 2007. This is also the rationale that party secretaries usually serve a five-year term. Fig. 4.4 shows the pattern and we find that there is an obvious five-year cycle of turnover time. Additionally, Fig. 4.5 is a map showing the distribution of political turnover of party secretary across cities in China over the period from 2003 to 2014.[150] The least number is 1 time and the most number is 6 times, while only three cities and two cities experience 1 political turnover and 6 political turnovers, respectively. Nearly half of the cities (143/304) have 3 political turnovers, which keeps pace with the three times of Congress during the period from 2003 to 2014. We also find that cities with more times are mostly distributed in the central and western provinces. Specifically, in all 88 cities with more than 3 times, 31 cities are located in the central provinces and 30 in the western provinces. The finding may be decided by that higher party organizations frequently appoint talented party cadres to the central and western provinces to boost the local economy. Additionally, since the political environment in the central and western provinces is poorly regulated, the probability of corruption and public disaster is higher. For example, the most corrupt province in China is Shanxi Province which is one of the central provinces. The national

[150] For Table 4.1 and Fig. 4.1, we use the number of cities each year in the sample to calculate the ratio of political turnovers. However, for Fig. 4.5, if we choose the number of cities each year in the sample to calculate the number of political turnovers for each city during the period from 2003 to 2014, a statistical error may occur. Specifically, in 2010 Lhasa is not included in the sample since the *China City Statistical Yearbook* does not record the data of Lhasa in 2010, while in other years Lhasa is included in the sample. Additionally, the data of county-level cities directly governed by provincial governments is available from 2011, so these county-level cities are not included in the sample before 2011. These cities (Lhasa and county-level cities) are not included in the sample in some years but may experience political turnovers in these years. Thus, as long as a city has been in the sample, we calculate the number of political turnovers of it during the period from 2003 to 2014 to make Fig. 4.5.

'Antigraft Campaign' in 2014 removed 15,450 government officials including seven provincial officials in Shanxi Province.[151]

[*Insert Fig. 4.4 here*]

[*Insert Fig. 4.5 here*]

4.6. Model specifications and summary statistics

4.6.1. Model specifications

In the study, we choose a modified Euler equation. The Euler equation has been widely used to test the existence of financial constraints on firms' investments (Whited, 1992; Bond et al., 2003), which has an advantage of a dynamic structural model to control expected firms' future profitability. We modify the Euler equation as shown in Eq. (4.1).

$$Log\ (Pat_{i,t} + 1) = \beta_1 Log\ (Pat_{i,t-1} + 1) + \beta_2 Log\ (Pat_{i,t-1} + 1)^2 + \beta_3 Sa_{i,t-1} + \beta_4 Cf_{i,t-1} + \beta_5 Dbt_{i,t-1} + \beta_6 FinDev_{i,c,t-1} + \beta_7 PT_{i,c,t-1} + V_i + V_t + V_o + V_j + V_p + e_{i,t} \quad (4.1)$$

where the dependent variable $Log\ (Pat_{i,t} + 1)$ is the natural logarithm of the number of patent applications per firm. $FinDev_{i,c,t-1}$ and $PT_{i,c,t-1}$ are our main explanatory variables, representing city-level financial development and local political turnover. As regards other control variables, $Sa_{i,t-1}$ is the ratio of firms' cash flows to total assets. $Cf_{i,t-1}$ is the ratio of

[151] *The Quartz*, 'China's corruption crackdown is so vast, top officials from every single province have been nabbed', Nov. 13th, 2015. https://qz.com/547695/chinas-corruption-crackdown-is-so-vast-top-officials-from-every-single-province-have-been-nabbed/.

firms' cash flows to total assets, showing the effect of firms' internal financing on innovation.[152] $Dbt_{i,t-1}$ can reflect the effect of long-term debts on innovation, measured by the ratio of firms' new long-term debts to total assets (Guariglia & Liu, 2014).[153] We choose lagged terms $(t-1)$ of the independent variables to avoid simultaneity issues, which can alleviate the reverse causality between $Log\ (Pat_{i,t}+1)$ and the independent variables. Additionally, since R&D achievements need a long-term cycle, innovation is largely affected by previous financial variables. We winsorize all firm-level continuous regression variables at the 1% tails to minimize the potential influence of extreme values.[154] V_i is a firm fixed effect. V_t is a year fixed to control effect time-varying movements in the economic cycle. V_o is a set of six ownership dummy variables to control the ownership effect.[155] V_j and V_p are industry dummy variables and geographical dummy variables.[156] $e_{i,t}$ is an idiosyncratic error term. The subscripts i is firm, c city, t year, o ownership, j industry and p province.

According to our Hypothesis 1, if city-level financial development encourages firms' innovation activities, the marginal effect of $FinDev_{i,c,t-1}$, β_6, should be positive and

[152] Cash flows is the sum of net profits and current depreciation. However, the data of current depreciation is missing in 2008 and 2009 in the NBS firm-level data. Considering that net profits is the main source of internal financing, we have to use net profits to replace cash flows in 2008 and 2009.

[153] Since R&D project has characteristics of a long-term investment cycle and a huge fund demand, it is obvious that innovation is affected more by long-term debts. We also cover new short-term debts to make a robustness test in Section 4.8.4.

[154] Since the innovation variable, $Log\ (Pat_{i,t}+1)$, is a left-censored variables at zero, we only winsorize it at the 99% tail of the positive value. Considering that the number of patent applications per firm is a discrete variable, we make a robustness test if we do not winsorize the innovation variable and the estimation results keep consistent.

[155] The six ownership types are SOEs, foreign firms, private firms, collective firms, Hong Kong, Macao or Taiwan (HMT) firms, and mixed ownership firms, which is calculated on the majority of paid-in capitals.

[156] We construct the industry-specific component and the location-specific component by using 40 two-digit codes and 31 provincial codes. We obtain qualitatively same estimation results when we employ three-digit codes or four-digit codes, and city dummies to capture the industry effect and the location effect. For brevity we do no report them.

significant. If the marginal effect of $PT_{i,c,t-1}$, β_7, is positive and significant, we could verify our Hypothesis 2 that local political turnover promotes firms' innovation activities. To test our Hypothesis 3 whether political turnover affect the relationship between financial development and innovation, we augment Eq. (4.1) by adding the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, to get Eq. (4.2). We expect the marginal effect of $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, β_8, is negative and significant according to Hypothesis 3. Other variables and subscripts in Eq. (4.2) are the same as those in Eq. (4.1).

$$\begin{aligned} Log\ (Pat_{i,t}+1) = {} & \beta_1 Log\ (Pat_{i,t-1}+1) + \beta_2 Log\ (Pat_{i,t-1}+1)^2 + \beta_3 Sa_{i,t-1} + \\ & \beta_4 Cf_{i,t-1} + \beta_5 Dbt_{i,t-1} + \beta_6 FinDev_{i,c,t-1} + \beta_7 PT_{i,c,t-1} + \\ & \beta_8 FinDev_{i,c,t-1} * PT_{i,c,t-1} + V_i + V_t + V_o + V_j + V_p + e_{i,t} \qquad (4.2) \end{aligned}$$

4.6.2. Summary statistics

In the section, we summarize the main regression variables and other related variables for the full sample, firms with/without patent applications.[157] Table 4.2 reports the means and medians (in parentheses) of the main regression variables and related variables. The number of firms with patent applications is 124,895, roughly 7.561% of the full sample, showing a low enthusiasm of Chinese firms in patenting activity. For financial development ($FinDev_{i,c,t-1}$), we find that the average values of three ratios for firms with patent applications (117.646%, 165.907% and 69.879%) are all higher than those for firms without patent applications (97.622%, 141.471% and 67.912%). This finding may indirectly prove a positive relationship between financial development and innovation. The average value of political turnover

[157] We summarize the number of observations estimated into regressions. This is the reason that the number of total observations is 1,651,881. If we summarize the number of all observations in the panel (3,160,672), the findings keep qualitatively same.

($PT_{i,c,t-1}$) for firms with patent applications (28.622%) is greater than that for firms without patent applications (26.527%), suggesting that innovation activities may be positively correlated with local political turnover. The mean values of the ratio of sales to total assets ($Sa_{i,t-1}$) and the ratio of cash flows to total assets ($Cf_{i,t-1}$) are both lower for firms with patent applications (165.297% and 10.987%) than firms without patent applications (261.108% and 13.600%), while the mean value of the ratio of new long-term debts to total assets ($Dbt_{i,t-1}$) is higher for firms with patent applications (0.426%) than firms without patent applications (0.229%). The finding could be explained by that external finance plays an important role in innovation activities due to the high demand for external funds of R&D. As regards other variables, average values of real total assets and age are higher for innovative firms (729.123 million CNY and 13.040 years old) than non-innovate counterparts (118.023 million CNY and 10.693 years old), showing that innovate firms are larger and more mature. It is not surprising that large and mature firms generally have a greater ability to invest in R&D projects. The lower average value of political affiliation for firms with patent applications (78.104) shows innovative firms are more politically affiliated compared to non-innovate firms (whose corresponding value is 80.698).[158] Firms with patent applications have more percentage of state shares (average value is 4.802%) than counterparts without patent applications (average value is 4.156%). Firms with patent applications are more likely to be distributed in the eastern region (average value is 1.290) compared to firms without patent applications (average value is 1.338). All variable definitions are shown in Appendix D.

[*Insert Table 4.2 here*]

[158] Appendix D shows that the index of political affiliation is a categorical variable. In the dataset, the Chinese appellation of political affiliation is 'zhengzhilishu'. If the value of 'zhengzhilishu' for one firm is higher, the firm is politically affiliated at a lower level.

4.7. Estimation methodology and empirical results

4.7.1. Estimation methodology

In the study, considering that the dependent variable, $Log\ (Pat_{i,t} + 1)$ is a typical left-censored variable (around 93.91% of sample firms have no patent applications), we use a Tobit estimation. Theoretically, we should employ the Random-effects Tobit estimator due to the firm heterogeneity (Tobin, 1958). However, due to a large panel of firms (the number of observations into estimation is 1,651,881), the processing time of a Random-effects estimation is very time-consuming[159]. We have to use the Pooled Tobit for time-saving instead. We then report marginal effects instead of coefficients for the Tobit estimation. According to Cong (2001), the marginal effect of the Tobit estimator includes three types: marginal effect on the probability of being uncensored with respect to the change of regressors; marginal effect on the quantity of truncated data with respect to the change of regressors; marginal effect on the quantity of censored data with respect to the change of regressors.[160]

4.7.2. Empirical results

Table 4.3 shows the estimation results of baseline Eq. (4.1) using the Pooled Tobit for the full sample. Columns (1) to (9) correspond to the three indicators of city-level financial development, i.e., the *credit ratio*, the *deposit ratio* and the *saving ratio*. We find that city-level financial development encourages firms' innovation activities in both the likelihood and

---

[159] The processing time of a Random-effects estimation based on our sample is over ten hours, we thus have to employ the Pooled Tobit. To ensure robustness, we take some tests of the Random-effects estimation for the full sample and the results keep qualitatively to those of the Pooled Tobit estimation.

[160] Truncated data is the subsample whose dependent variables is not censored; censored data is all observations in the sample no matter the dependent variable is censored or not censored.

intensity. The average marginal effects of $FinDev_{i,c,t-1}$ on $Log\ (Pat_{i,t} + 1)$ are all positive and significant at the 1% level. Specifically, in columns (1) to (3), the marginal effect in the probability of $FinDev_{i,c,t-1}$ is 1.149% (*credit ratio*), 1.034% (*deposit ratio*) and 0.960% (*saving ratio*) respectively, suggesting that an 10% increase in $FinDev_{i,c,t-1}$ is associated with an increase of 0.115%, 0.103% and 0.096% in the probability that firms have patent applications. In columns (4) to (6), the marginal effect in the quantity of truncated data of $FinDev_{i,c,t-1}$ is 3.530% (*credit ratio*), 3.179% (*deposit ratio*) and 2.952% (*saving ratio*) respectively, which means that a 10% increase in $FinDev_{i,c,t-1}$ makes an increase of 0.353%, 0.318% and 0.295% in $Log\ (Pat_{i,t} + 1)$ for only firms with patent applications. In columns (7) to (9), the marginal effect in the quantity of censored data of $FinDev_{i,c,t-1}$ is 1.859% (*credit ratio*), 1.674% (*deposit ratio*) and 1.555% (*saving ratio*) respectively, showing that as $FinDev_{i,c,t-1}$ rises by 10%, $Log\ (Pat_{i,t} + 1)$ increases by 0.186%, 0.167% and 0.156% respectively for firms with/without patent applications. The estimation results confirm our Hypothesis 1 that there is a positive and significant relationship between city-level financial development and firms' innovation activities in both probability and quantity. The financial market is positively associated with firms' innovation activities in China. The results suggest that Chinese firms benefit from an increase in financial development by meeting their fund demands for R&D.

[*Insert Table 4.3 here*]

For political turnover, regardless of the measure of financial development, we observe that the average marginal effects of the political turnover variable, $PT_{i,c,t-1}$, are all positive and significant. Since $PT_{i,c,t-1}$ is a binary variable to indicate local political turnover, the marginal effect of $PT_{i,c,t-1}$ is the effect when $PT_{i,c,t-1}$ changes from 0 to 1. Specifically, in columns (1) to (3), the average marginal effect in the probability of $PT_{i,c,t-1}$ is 0.092%, 0.106% and 0.073%

respectively, which means as $PT_{i,c,t-1}$ becomes from 0 to 1, the probability that firms have patent applications would increase by 0.092%, 0.106% and 0.073%. In columns (4) to (6), the average marginal effect in the quantity of truncated data of $PT_{i,c,t-1}$ is 0.282%, 0.326% and 0.225% respectively, suggesting that as $PT_{i,c,t-1}$ becomes from 0 to 1, $Log\ (Pat_{i,t}+1)$ grows by 0.282%, 0.326% and 0.225% respectively for only firms with patent applications. In columns (7) to (9), the average marginal effect of $PT_{i,c,t-1}$ is 0.148%, 0.172% and 0.118% separately in the quantity of censored data, showing that when $PT_{i,c,t-1}$ transfers from 0 to 1, $Log\ (Pat_{i,t}+1)$ rises by 0.148%, 0.172% and 0.118% separately for all observations in the estimation. The estimation results support our Hypothesis 2 according to which local political turnover promotes firms' innovation activities in China in both probability and quantity. Local political turnover may create more innovation opportunities and stimulate firms to innovate.

As regards control variables, the average marginal effects of $Log\ (Pat_{i,t}+1)$ are all positive and significant at the 1% level and the average marginal effects of $Log\ (Pat_{i,t-1}+1)^2$ are all negative and significant at the 1% level, which stays in step with the theoretical assumption. Short-sighted behaviours of firms in China may interpret the negative and significant marginal effects of $Sa_{i,t-1}$, showing that firms may become more conservative with increased performance. The average marginal effects of $Cf_{i,t-1}$ and $Dbt_{i,t-1}$ are all positive and significant, while the magnitude of the marginal effect of $Cf_{i,t-1}$ is greater than that of $Dbt_{i,t-1}$ no matter in which column. The finding verifies the pecking order theory (Myers & Majluf, 1984) that internal finance is preferred when firms finance innovation. The positive and significant marginal effects of $Dbt_{i,t-1}$ suggest that long-term external finance plays an important role in financing innovation due to the high demand funds of R&D.

Table 4.4 reports the estimation results of Eq. (4.2) which includes the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, to test Hypothesis 3. No matter which proxy of financial development used in the regressions, we find that the average marginal effects of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, are all negative and significant at the 1% level, showing that $PT_{i,c,t-1}$ decreases the positive effect of $FinDev_{i,c,t-1}$ on $Log\ (Pat_{i,t}+1)$. The marginal effect of the interaction term is calculated as the difference between the average marginal effect of $FinDev_{i,c,t-1}$ evaluated at 0 of $PT_{i,c,t-1}$ and the average marginal effect of $FinDev_{i,c,t-1}$ fixed at 1 of $PT_{i,c,t-1}$. Specifically, in columns (1) to (3), the marginal effect in the probability of the interaction term is -0.283%, -0.236% and -0.748% respectively, suggesting that as $PT_{i,c,t-1}$ becomes from 0 to 1, the positive effect of $FinDev_{i,c,t-1}$ in the probability that firms have patent applications reduces by 0.283%, 0.236 and 0.748% respectively. In columns (4) to (6), the marginal effect in the quantity of truncated data of the interaction term is -0.892%, -0.747% and -2.307% respectively, showing that when $PT_{i,c,t-1}$ changes from 0 to 1, the positive effect of $FinDev_{i,c,t-1}$ on $Log\ (Pat_{i,t}+1)$ decreases by 0.892%, 0.747% and 2.307% respectively for only firms with patent applications. In columns (7) to (9), the marginal effect in the quantity of censored data of the interaction term is -0.460%, -0.384% and -1.210% respectively, indicating that if $PT_{i,c,t-1}$ moves from 0 to 1, the positive effect of $FinDev_{i,c,t-1}$ on $Log\ (Pat_{i,t}+1)$ drops by 0.460%, 0.384% and 1.210% respectively for all firms in the sample. The negative marginal effects of the interaction terms are in line with our Hypothesis 3 that the positive impact of financial development on innovation is reduced with political uncertainty. Additionally, we only focus on the marginal effect of the interaction term ($FinDev_{i,c,t-1} * PT_{i,c,t-1}$) of Eq. (4.2) as the marginal effects of the two single terms, $FinDev_{i,c,t-1}$ and $PT_{i,c,t-1}$, are not meaningful.

[*Insert Table 4.4 here*]

4.8. Endogeneity and robustness checks

Thus far in our main estimations, we assume that city-level financial development and local political uncertainty are exogenous to firm-level innovation, and then we have tested the positive effects of both financial development and political uncertainty on firms' innovation activities. However, it is still a concern that the estimation results face potential endogeneity issues caused by reverse causality, potential measurement errors and omitted variables. First, reverse causality could make that financial development and political uncertainty are endogenous to innovation if firms in one city become more involved in innovation activities. Specifically, a high level of innovation likely increases the amount of loans in the city due to the high funding demand of R&D. Innovative firms are more likely to make profits and have a stronger ability to deposit, which could increase the amount of deposits in the city. Additionally, local corporate innovation can promote economic performance, which is the most important evaluation indicator for local official's performance in China. Thus, the success of corporate innovation may trigger political turnovers of party secretaries. Although in regressions we have employed the lagged values of the independent variables, e.g., city-level financial development and local political uncertainty, to avoid the simultaneity issue, our empirical framework is not completely immune to the potential reverse causality. Thus, we employ an instrumental variable (IV) estimation to confirm the causality between financial development, political uncertainty and innovation. Second, we use alternative measures of financial development, political uncertainty and innovation to estimate again to eliminate the potential measurement errors. Third, we also include the contemporaneous terms of independent variables into regressions to avoid the estimation bias of potential omitted variables. Finally, we make an extension to test whether the moderating effect of political uncertainty on the positive relationship between financial development and innovation varies across turnover types of local government heads, firms' political connections and financial constraints.

4.8.1. Instrumental variable (IV) estimation

For identifying the causal relationship between financial development and innovation and the causal relationship between political turnover and innovation, we employ an instrumental variable estimation. We apply the fraction of senior citizens in a given province-year ($Senior_{p,t}$) as the instrumental variable for financial development (Becker, 2007; Butler & Cornaggia, 2011). Because seniors tend to consume less while deposit more compared to young people, a large fraction of seniors in a region probably leads to more financial supplies instead of financial demands. For the political turnover variable, we construct a dummy variable, $PT5_{c,t}$, as its instrumental variable. Specifically, $PT5_{c,t}$ takes a value of one for the fifth year after the year, $t-5$, when the city c experiences an official turnover of city party secretary, and zero otherwise. Since city party secretaries usually have a five-year cycle, $PT5_{c,t}$ can tease out economic factors and speculate only based on the past information of turnovers. For example, Shanghai, one of the four municipalities, experienced three turnovers of city party secretary in years 2003, 2007 and 2008, so $PT5_{c,t}$ for Shanghai equals 1 in years 2008 (2003 plus 5), 2012 (2007 plus 5), 2013 (2008 plus 5), and equals 0 in other years. The instrumental variable, $PT5_{c,t}$, is not related to the innovation variable, $Log\ (Pat_{i,t}+1)$, but positively related to the political turnover variable, $PT_{i,c,t}$. Since we used the lagged values of independent variables in regressions, we instrument the financial development variable by employing the lagged values of $Senior_{p,t}$ and $PT5_{c,t}$ together.

Table 4.6 shows the estimation results of IV Tobit. In columns (1) to (3), the average marginal effects of the instrumented financial development variable, $FinDev_{i,c,t-1}$, and the average marginal effects of the instrumented political turnover variable, $PT_{i,c,t-1}$, are positive and significant. The findings confirm the positive causal effects of financial development and political turnover on innovation. In columns (4) to (6), the marginal effects of the instrumented interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, are negative and significant. To check the validity of the instrumental variables, we make a set of tests. Specifically, the F-values in the first stage are much larger than the thumb of 10, suggesting that the estimation bias from potential weak instruments does not exist for the two instrumental variables (Stock & Yogo, 2005). Since we have two instrumented variables and the instrumented interaction term, for brevity we do not show the estimation results of the first-stage (Newey, 1987).[161] The coefficient values of the instrumental variables $Senior_{p,t}$ and $PT5_{c,t}$ keep consistent with our theoretical assumptions. Next, we conduct a Wald test of exogeneity and an Anderson-Rubin (AR) test.[162] We find that the p-value statistics of the Wald test are significant (0.000), suggesting that the regressors are endogenous and the adaption of IV estimation is essential. The p-value statistics of the AR test are also significant (0.000), showing that the model is identified and/or the instrumental variables are effective. Furthermore, the additional estimation results of a Hausman test and a Smith-Blundell test verify the existence of endogenous variables in the regressions.

[*Insert Table 4.5 here*]

4.8.2. Alternative measures of financial development, political turnovers and innovation

In the section, we make robustness tests using alternative measures of financial development, political turnovers and innovation to alleviate potential measurement errors. For brevity, we only report the estimated average marginal effects in the quantity of censored data

---

[161] For estimating the first-stage results, we have to use the code 'ivtobit' with the option of 'twostep' in STATA based on Newey's two-step method. For the second-step estimation results, we adapt the default estimator of maximum likelihood without the option of 'twostep'.

[162] Wald test examines whether the error terms in the structural equation are correlated to the residuals from the reduced-form equation for the endogenous variables. AR test is a joint test of the structural parameter and the exogeneity of instrumental variables. Its null hypothesis is that all regressors are exogenous and all the minimum canonical correlation is zero. Thus, if the results of Wald test and AR test are significant, suggesting the null hypothesis that all independent variables in regressions are exogenous is not accepted.

of the single terms, $FinDev_{i,c,t-1}$ and $PT_{i,c,t-1}$, and the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$. Panel A of Table 4.6 shows the estimation results of Eqs. (4.1) and (4.2) when we measure financial development, $FinDev_{i,c,t-1}$, by using the three ratios (*credit ratio*, *deposit ratio* and *saving ratio*) based on the data of municipal districts for each city. Since municipal districts are the core components where economic activities including lending and borrowing events happen, the measure of financial development based on municipal districts can better reflect the influence of the main financial systems of cities. In columns (1) to (3), the average marginal effects of $FinDev_{i,c,t-1}$ and $PT_{i,c,t-1}$ are still positive and significant. In columns (4) to (6), the marginal effects of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, keep negative and significant. Our findings remain the same when the measure of financial development is based on municipal districts.

[*Insert Table 4.6 here*]

Panel B of Table 4.6 presents the estimation results of Eqs. (4.1) and (4.2) when we use political turnovers in calendar years to construct the dummy variable, $PT_{i,c,t}$. Additionally, Panel C of Table 4.6 reports the estimation results of Eqs. (4.1) and (4.2) when we tease out predictable political turnovers to construct the dummy variable, $PT_{i,c,t}$. Since city party secretaries usually serve one term (five years), the political turnovers that occur in the last year of terms can be largely predicted by market participates. These political turnovers may not affect corporate innovation. We can find that in both Panel B and Panel C, the average marginal effects of the single terms, $FinDev_{i,c,t-1}$ and $PT_{i,c,t-1}$, in columns (1) to (3) are positive and significant, and the marginal effects of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, in columns (4) to (6) hold negative and significant. The results keep qualitatively unchanged when we take alternative measures of local political turnover.

Table 4.7 reports the estimation results of Eqs. (4.1) and (4.2) when we use alternative measures of innovation. We only report the average marginal effects in the quantity of censored data of the variables, $FinDev_{i,c,t-1}$, $PT_{i,c,t-1}$, and $FinDev_{i,c,t-1} * PT_{i,c,t-1}$. Specifically, Panel A of Table 4.7 shows the estimation results when the innovation variable is measured by the number of invention patent applications, since invention patents are patents with good technology which require the most innovative efforts (Li, 2012). Panel B of Table 4.7 displays the estimation results when the innovation variable is measured by the number of patents applied independently. As compared to joint patent applications, independent patent applications can better reflect the innovation capability at the individual level and avoid disturbance from other firms' innovation ability. Panel C of Table 4.7 exhibits the estimation results when the innovation variable is measured by the number of patents granted since not all patents applied can be granted. We can find that no matter which one measure of innovation, in columns (1) to (3) the marginal effects of the financial development variable, $FinDev_{i,c,t-1}$, and the political turnover variable, $PT_{i,c,t-1}$, keep positive and significant; in columns (4) to (6) the marginal effects of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ maintain negative and significant. The estimation results remain consistent when we use other patent indicators to measure innovation.

[*Insert Table 4.7 here*]

4.8.3. Augmented specification with contemporaneous terms

The last concern of endogeneity is the estimation bias of potential omitted variables in regressions. At the right side of regressions, we only cover the lagged terms as the independent variables to avoid the simultaneity issue. However, the contemporaneous terms of independent variables possibly affect the contemporaneous term of innovation at the left side of regressions. Hence, following Brown et al. (2009) and Guariglia and Liu (2014), we add the contemporaneous terms of independent variables to augment regressions to address the concern of potential omitted variables.

Table 4.8 provides the corresponding estimation results of Eqs. (4.1) and (4.2). For brevity, we only report the average marginal effects in the quantity of censored data. Specifically, we first include the contemporaneous terms of financial development variable, $FinDev_{i,c,t}$, and political turnover variable, $PT_{i,c,t}$, and into Eq. (4.1) to explore the effect of contemporaneous financial development and contemporaneous political turnover on innovation. In columns (1) to (3), the sum of the marginal effects of financial development variables ($FinDev_{i,c,t}$ and $FinDev_{i,c,t-1}$) and the sum of the marginal effects of political turnover variables ($PT_{i,c,t}$ and $PT_{i,c,t-1}$) are both positive and significant. Additionally, we find that the positive marginal effects of the lagged financial development variable, $FinDev_{i,c,t-1}$, and the lagged political turnover variable, $PT_{i,c,t-1}$, are all greater and more significant than those of the contemporaneous financial development variable, $FinDev_{i,c,t}$, and the contemporaneous political turnover variable, $PT_{i,c,t}$. The finding indirectly verifies that R&D projects are largely affected by previous financial development and political turnover. Second, besides the two contemporaneous single terms, we further put the contemporaneous interaction term, $FinDev_{i,c,t} * PT_{i,c,t}$, into Eq. (4.2) to capture the effect of contemporaneous political turnover on the relationship between contemporaneous financial development and innovation. However, in columns (4) to (6), the marginal effects of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, are negative and significant, while the marginal effects of the interaction term, $FinDev_{i,c,t} * PT_{i,c,t}$, are insignificant. The findings not only keep consistent with our main empirical findings but also confirm that innovation is mainly affected by past political turnover and past financial development. The contemporaneous terms of other financial variables are also included in regressions.

[*Insert Table 4.8 here*]

4.8.4. Other robustness tests

Besides the above tests, we make more robustness tests and the corresponding estimation results are shown in Table 4.9. For brevity, we only report the average marginal effects in the quantity of censored data when financial development is calculated as the *credit ratio*. First, in columns (1) and (2) we drop firms with sales of less than 20 million CNY to re-estimate. Since the threshold for inclusion of the ‘above-scale’ enterprises is raised from 5 million CNY to 20 million CNY in the year 2011, dropping observations with sales of less than 20 million CNY could keep data consistency. Second, following Xu et al., (2016), in columns (3) and (4) we delete firms located in four municipalities and county-level cities to estimate since it could be argued that these cities are probably different from prefecture-level cities. Specifically, because four municipalities are directly governed by the central government instead of any provincial governments, political turnovers of city party sectary in four municipalities might be not decided by local factors but also by national political factors. Additionally, political turnovers of city party secretaries in county-level cities may have little impact on local enterprises due to a low administrative level. Since the information on county-level cities in *China City Statistical Yearbook* is only available from 2011, dropping county-level cities also can keep data of city consistency. Third, following An et al., (2016), in columns (5) and (6) we exclude firms in the years 2003, 2008, and 2013 to avoid the effect of the National Congress in the years 2002, 2007, and 2013. Dropping firms in the three years could address the concern that firms may adjust their innovation investments in anticipation of the National Congress and any resulting political turnovers.[163] Fourth, short-term debts may have

[163] An et al. (2016) remove the observations in the years 2002 and 2007 to avoid the national-election-year effect. However, considering that we use exact dates to capture political turnovers and the majority of political turnovers in national-election years (2002, 2007, and 2012) occur in the second half of the years or the first half of the

a potential effect on corporate innovation. To take the issue into account, in columns (7) and (8) we include the change of firms' short-term debts into our regressions to estimate. We find that the marginal effects of new long-term debts ($Dbt_{i,t-1}$) are greater than those of new short-term debts ($ShortDbt_{i,t-1}$), which is in line with the characteristic of R&D projects that innovation is largely affected by long-term debts instead of short-term debts. Fifth, in columns (9) and (10) we choose the Zero-inflated Poisson method to estimate since the patent variable $Pat_{i,t}$ (the number of patent applications per firm) is a count variable. In the main empirical results, we use the Tobit estimation method considering that more than 93% of firms in the sample do not have patent applications so the dependent variable $Log\ (Pat_{i,t}+1)$ is a left-censored variable. Last, in columns (11) and (12) we employ the Probit method to estimate if we use a binary variable to construct the innovation variable ($Pat_{i,t}$ equals 1 for firms with patent applications and equals 0 for firms without patent applications). The estimation results of the robustness tests remain qualitatively unchanged.

[*Insert Table 4.9 here*]

4.9. Further tests

In the section, we make additional analysis to test whether the moderating effect of political turnover on the positive impact of financial development on innovation would change across different turnover types, firms' political connection and firms' financial constraints. Table 4.10 reports the corresponding estimation results of Eq. (4.2). For brevity, we only report the average marginal effects in the quantity of censored data when financial development is

following years (2003, 2008, and 2013), we delete firms in the years 2003, 2008, and 2013 to better avoid the effect of National Congress.

proxied by *credit ratio*. Since we use lagged terms of independent variables in regressions, we also use lagged values of related variables to divide the sample into groups. All variable definitions and classification standards are shown in Appendix D.

[*Insert Table 4.10 here*]

4.9.1. Turnover types

We further explore the moderating effect of political turnover based on turnover types. Panel A of Table 4.10 shows the estimation results. Specifically, we expect the moderating effect should be more pronounced when an increase in political uncertainty, which is associated with unexpected turnover. First, we compare the group of firms in cities whose party secretaries are in around predicted turnover years of their terms and the group of firms in cities whose party secretaries are not in around predicted turnover years of their terms. Since the length of one term for one city party secretary is usually five years, we can regard the political turnovers when secretaries leave their posts in the years around the fifth year (4^{th}, 5^{th}, 6^{th}) of their terms as normal turnovers and others as abnormal turnovers.[164] In column (1) and (2), we find that the marginal effect of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ is negative and significant for firms in cities whose party secretaries are not in years around the 5^{th} year of their terms (-0.392%), while insignificant for firms in cities whose party secretaries are in years around the 5^{th} year of their terms. The results suggest that the negative effect of political turnover is more pronounced for firms facing abnormal turnovers. The interpretation is that compared to normal

[164] For the judgement of tenure years, as similar as the construction of the political turnover dummy variable, $PT_{i,c,t}$, we use the exact dates of turnovers to determine the tenure years. For example, Yun Gongmin and Shen Weichen, are former city party secretaries of Taiyuan (capital city of Shanxi Province). Yun Gongmin took office in September 2001 and left office in January 2006. Shen Weichen took office in January 2006 and left office in September 2010. Their tenure lengths are 4 years and 4 months, and 4 years and 8 months respectively, so we determine that they left their posts in the fifth year of their terms. We regrad these two turnovers as normal turnovers.

turnovers, abnormal turnovers have a larger shock on the financial market, so innovative firms might perceive the risk and invest less in R&D projects even they have access to finance. Therefore, the relationship between financial development and innovation could be attenuated due to abnormal political turnover.

Second, we test whether the moderating effect of political turnover is different between the group of firms in cities whose party secretaries are around predicted turnover ages and the group of firms in cities whose party secretaries are not around predicted turnover ages. According to an unwritten rule of the CPC, a party secretary of one prefecture-level city usually needs to promote or resign from a leading post when he reaches 55 years old, so there is a large probability of turnover when he is around 55 years old (54, 55 and 56).[165] In columns (3) and (4), we find that the marginal effect of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ is negative and significant for firms in cities whose party secretary turnover are not around predicted turnover ages (-0.701%) but insignificant for firms in cities whose party secretary turnover are around predicted turnover ages.

Third, we explore what changes to the moderating effect of political uncertainty across tenure lengths of party secretaries. We divide the full sample into the group of firms in cities whose party secretaries have been working with a short tenure length and the group of firms in cities whose party secretaries have been working with a long tenure length. We classify a position period within 3 years as a short tenure and a position period of more than 3 years as a

[165] According to the regulation of the CPC, city party secretaries of four municipalities are not only provincial-level leaders but also deputy national-level leaders, so their retirement ages are normally around 65 years old; party secretaries of county-level cities directly governed by provincial governments usually promotes or moves to other posts at 50 years old. Thus, we use the ages around 65 years old (64, 65 and 66) as the predicted turnover ages for four municipalities, and the ages around 50 years old (49, 50 and 51) as the predicted turnover ages for county-level cities.

long tenure due to the regulation of the CPC.[166] In column (5) and (6), we find that the marginal effect of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ is negative and significant for firms in cities whose party secretaries have been working with a short tenure while insignificant for firms in cities whose party secretaries have been working with a long tenure.

The results suggest that the moderating effect of political turnover is greater if party secretary turnover is not around predicted turnover ages or during the early years of their terms. We can consider party secretaries leaving their posts away from 55 years old or within three years of current terms as abnormal turnovers, which leads to a higher degree of political uncertainty. According to Hypothesis 3 that political uncertainty can distort the positive relationship between financial development and innovation

4.9.2. Firms' political connections

We further test the moderating effect of political turnover based on firms' political connections. We expect that moderating effect of political turnover is more pronounced for politically connected firms as political connections can attenuate the positive relationship between financial development and innovation.

To this end, we divide the full sample into the group of firms with political connections and the group of firms without political connections based on ownership structure, political affiliation, and state shares. Panel B of Table 4.10 reports the estimation results and the detailed classification standards are shown in Appendix D. We find that the marginal effect of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, is negative and significant for all types of firms, while its magnitude for SOEs (-0.925%), firms with political affiliation (-0.497%) and firms

[166] One document issued by the CPC in 2006 states that if one official moves to a new position within three years of his current position, the tenure years cannot be regarded as one term. Only more than three years can be recorded as one term. The document could be viewed via: http://cpc.people.com.cn/GB/64093/64387/4671315.html.

with state shares (-0.845%) is greater than that for non-SOEs (-0.343%), firms without political connection (-0.402%) and firms without state shares (-0.319%). SOEs, firms with political affiliation and firms with state shares tend to be more politically connected with governments than non-SOEs, firms without political affiliation and firms without state shares. The results show that for firms with political connections, political turnover reduces more the positive effect of financial development on innovation activities. Thus, for these firms, local political uncertainty can distort more the positive effect of financial development on R&D.

4.9.3. Firms' financial constraints

We last investigate the moderating effect of political turnover based on firms' financial constraints. We divide the full sample into the group of firms with low financial constraints and high financial constraints according to firms' size, firms' age and firms' SA index.[167] Panel C of Table 4.10 reports the corresponding estimation results. We find that the marginal effect of the interaction term, $FinDev_{i,c,t-1} * PT_{i,c,t-1}$, is more negative for large firms (-0.412%), mature firms (-0.538%) and firms with a low SA index (-0.504%) than small firms (-0.336%), young firms (-0.333%) and firms with a high SA index (-0.254%). Compare to large firms, mature firms and firms with a low SA index, small firms, young firms and firms with a high SA index tend to be financially constrained. The results suggest that the moderating effect of political turnover is more pronounced for low financially constrained firms than high financially constrained firms. This could be interpreted as the fact low financially constrained firms gain more access to external finance. Political uncertainty caused by political turnovers of local leaders could harm these firms' access to finance for their R&D. In contrast, firms with

[167] SA index is an indicator to measure firms' financial constraints from Hadlock and Pierce (2010). The detailed information on the classification standards is shown in Appendix D.

more financial constraints have difficulties in accessing finance and the negative impact of political uncertainty should have less influence on these firms.

4.10. Conclusions

Employing a large panel of 739,672 industrial-firms linked with the data of 305 cities over the period from 2003 to 2014, we show that there is a positive relationship between city-level financial development and firms' innovation activities in China. We also find that local political turnover facilitates corporate innovation, while attenuates the positive effect of financial development on corporate innovation. The results keep consistent with those of various robustness tests. Further evidence shows that the negative effect of political uncertainty on the positive relationship between financial development and innovation is various according to turnover types, firms' political connections and firms' financial constraints.

The findings provide many policy implications. First, due to the significant and positive effect of financial development on corporate innovation, Chinese governments should deepen the reform of the financial system to efficiently allocate financial sources. Since innovation is one important factor to boost the economy, regional balance in financial development contributes to the innovation development in the central and western regions then promotes economic development. For example, in 2001 the central government issued the strategy for 'large-scale development of western China', which states to increase the fraction of concessional loans used in the western regions to boost the financial development in the western regions. The central government can use more similar regional favourable policies to boost financial development. Second, considering that political turnover promotes firms' innovation activities, it may be important for policymakers to find mechanisms to increase necessary political turnovers to stimulate corporate innovation. For example, in 2006 the CPC central committee issued a document that clearly states that officials at the county-level or above who have worked for a long time in current positions must be moved to new positions.[168] Third, political uncertainty arising from local political turnover could hurt the positive effect of financial development on corporate innovation, there should be more attention paid to changes in the political economy. Fourth, because the negative effect of political turnover on the positive relationship between financial development and innovation is strong for firms facing abnormal political turnovers, firms with political connections and firms are less financially constrained, governments should use some policy tools to monitor the borrowing and lending market to keep financial stability during the periods of political turnovers and implement policy schemes to ensure these firms' external financing sources stable. Additionally, governments should use policies to encourage these firms to reduce their overwhelming dependence on external finance.

[168] The official name of the document is 'Interim provisions on the term of office of Party and government cadres'. The Chinese source text could be view via: http://cpc.people.com.cn/GB/64093/64387/4671315.html.

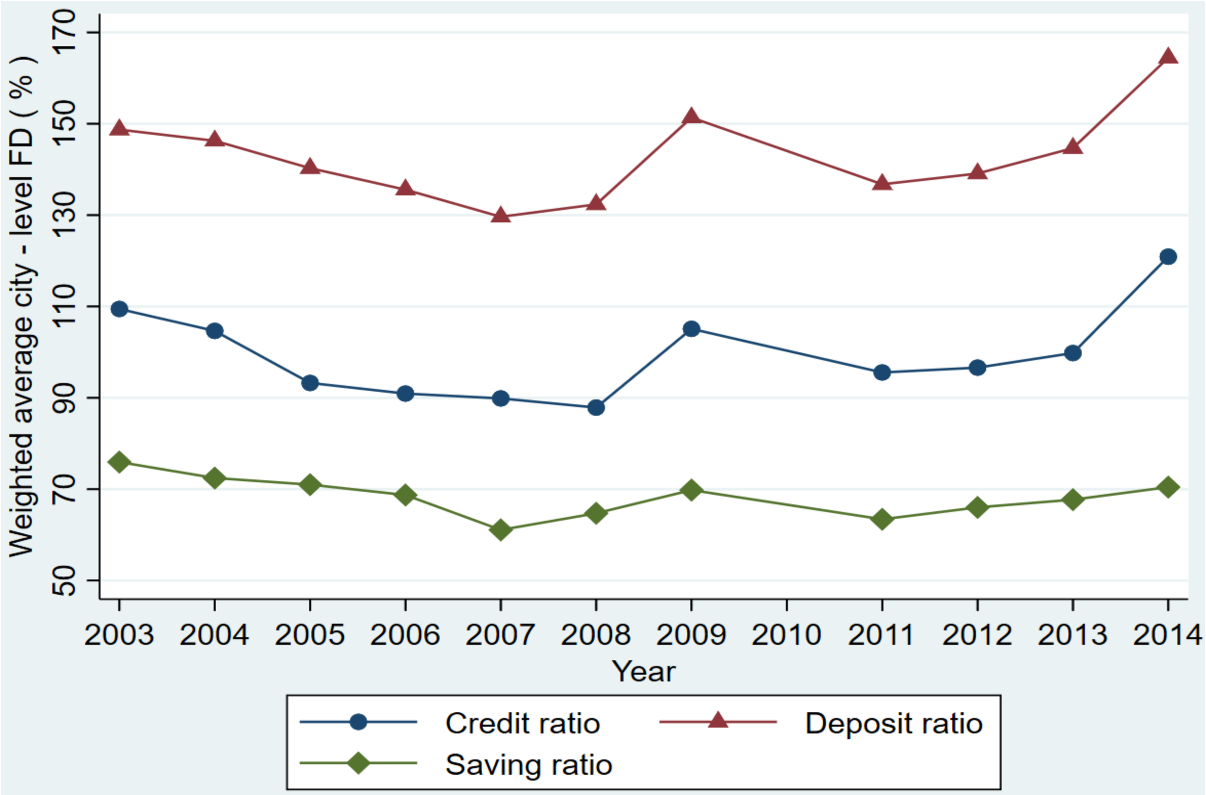


Figure 4.1. Trend line of weighted average city-level FD in China from 2003 to 2014

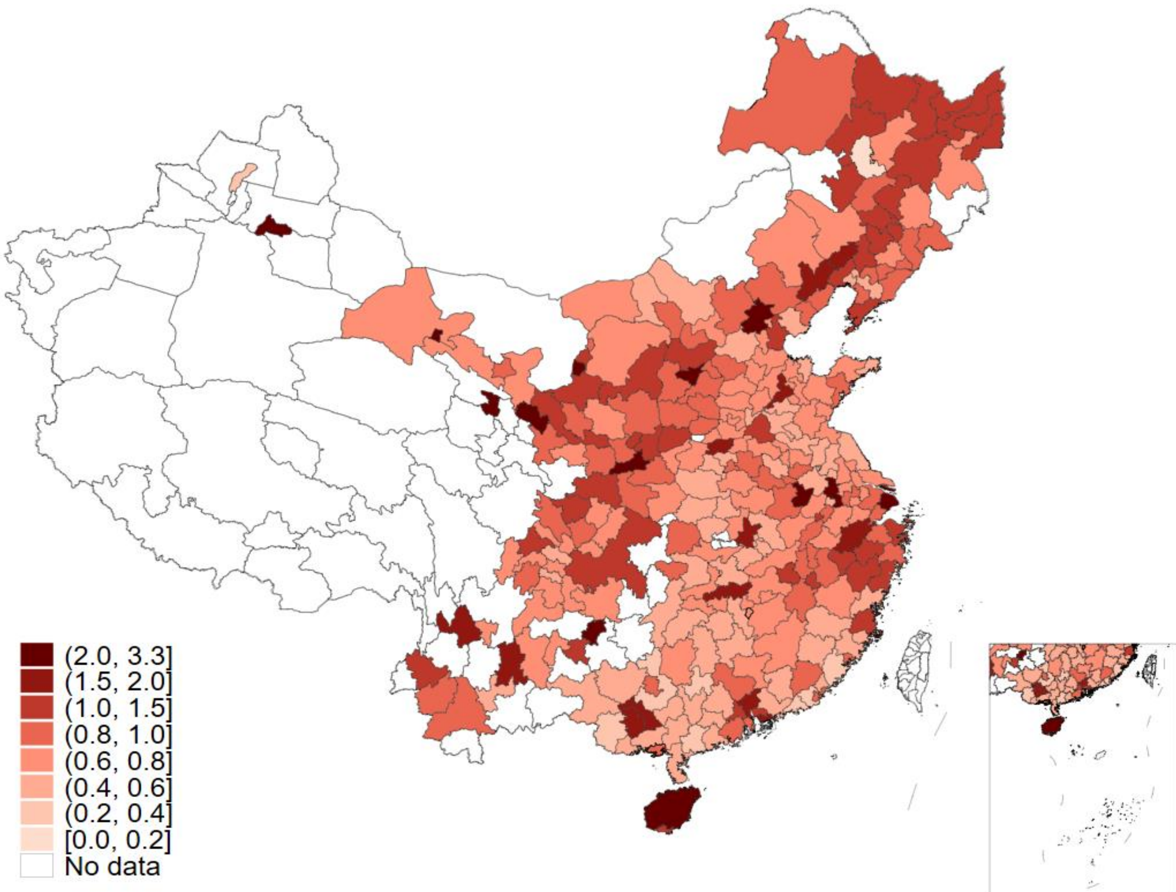


Figure 4.2. City-level financial development in China in 2003

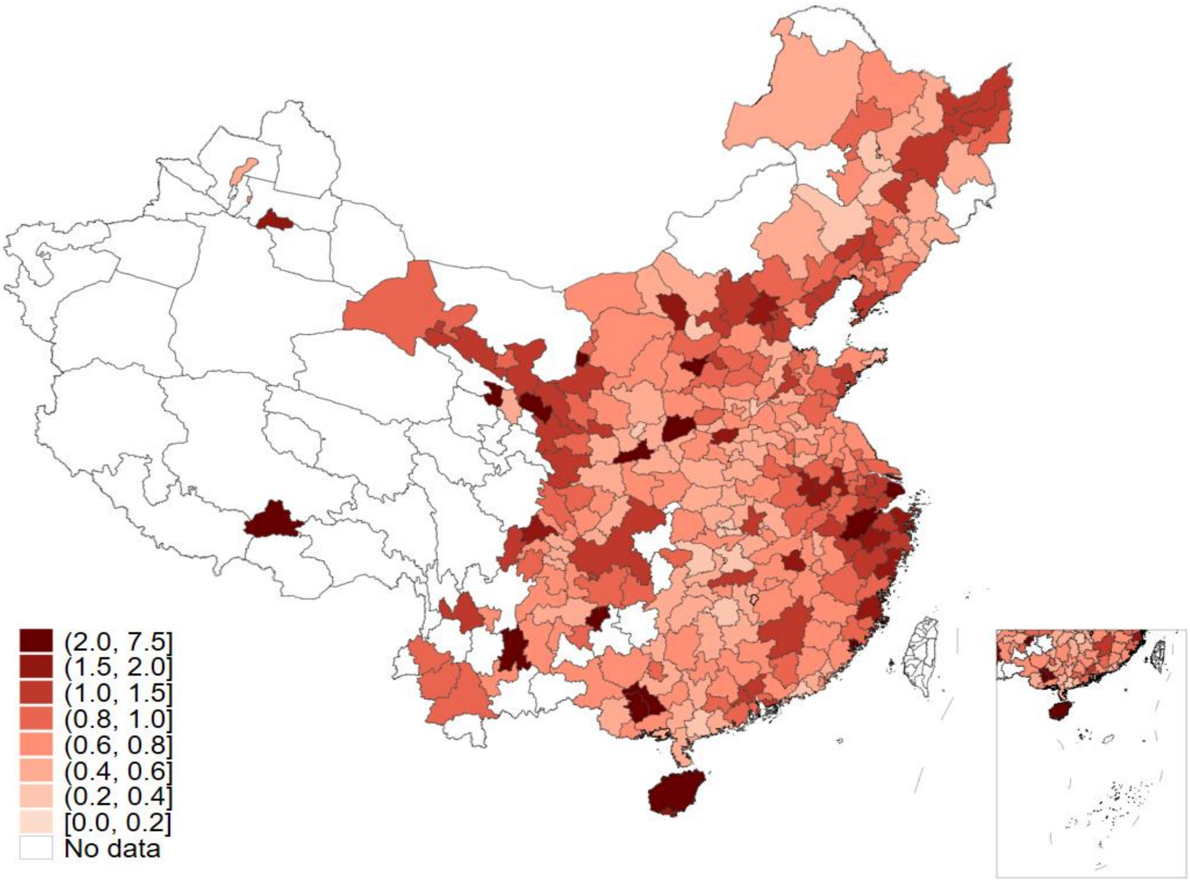


Figure 4.3. City-level financial development in China in 2014

Figure 4.4. Trend line of turnover ratio of city party secretary in China from 2003 to 2014

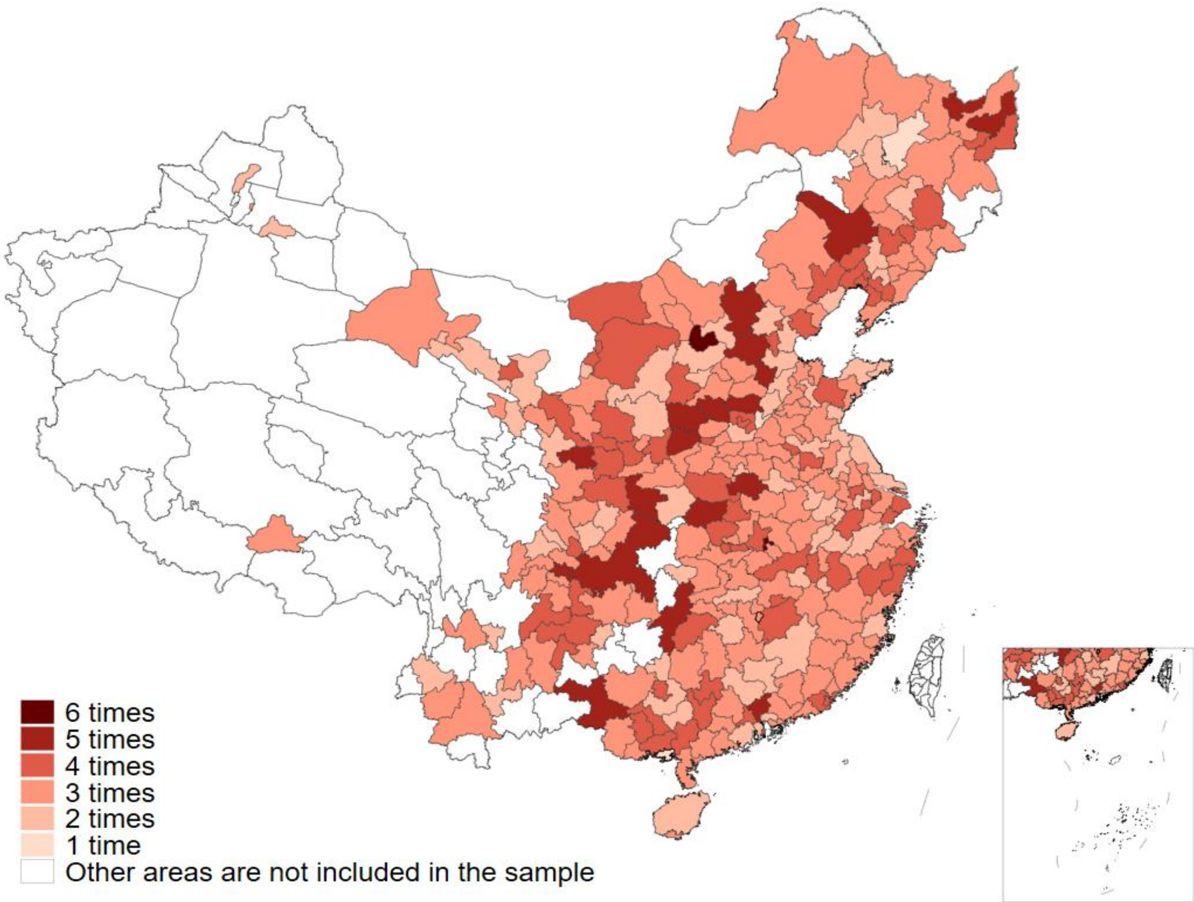


Figure 4.5. Number of political turnovers of city party secretary in China from 2003 to 2014

Table 4.1

Distribution of the sample observations in years

Year	Number of observations	Number of observations with patent applications	Percentage of observations with patent applications (%)	Weighted average city-level FD (%)			Number of sample cities	Number of political turnovers	Ratio of political turnovers (%)
				Credit ratio	Deposit Ratio	Saving ratio			
2003	168,858	4,006	2.37	109.45	148.72	75.94	284	114	40.14
2004	257,138	5,625	2.19	104.65	146.27	72.45	286	48	16.78
2005	253,646	6,221	2.45	93.26	140.28	71.00	286	64	22.38
2006	284,613	7,780	2.73	90.93	135.57	68.73	286	60	20.98
2007	323,672	9,468	2.93	89.87	129.64	61.09	287	79	27.53
2008	397,721	14,361	3.61	87.87	132.35	64.72	287	126	43.90
2009	311,945	15,405	4.94	105.09	151.36	69.80	287	33	11.50
2010	/	/	/	108.41	153.16	68.07	286	36	12.59
2011	297,670	26,804	9.00	95.55	136.75	63.42	302	81	26.82
2012	318,424	34,897	10.96	96.61	139.10	66.02	302	106	35.10
2013	337,343	39,568	11.73	99.81	144.66	67.71	303	116	38.28
2014	209,642	31,438	15.00	120.90	164.44	70.45	304	46	15.13
Total	3,160,672	195,573	6.19	100.20	143.52	68.28	3,500	909	25.97

Notes: At the last row, the total percentage of observations with patent applications is the value of the total number of observations with patent applications (195,573) divided by the total number of observations (3,160,672); the total weighted average city-level FD is the mean value of weighted average city-level FD each year; the total ratio of political turnovers is the value of the total number of political turnovers (909) divided by the total number of sample cities (3,500).

Table 4.2

Summary statistics-sample means and medians (in parentheses)

	Full sample	Firms with patent applications $[Log\ (Pat_{i,t}+1)>0]$	Firms without patent applications $[Log\ (Pat_{i,t}+1)=0]$	*Diff*
Main regression variables				
$FinDev_{c,t-1} - Credit\ ratio$	99.136	117.646	97.622	0.000
	(84.287)	(111.270)	(83.446)	
$FinDev_{c,t-1} - Deposit\ ratio$	143.318	165.907	141.471	0.000
	(128.515)	(149.158)	(125.876)	
$FinDev_{c,t-1} - Saving\ ratio$	68.061	69.879	67.912	0.000
	(64.780)	(66.115)	(64.610)	
$PT_{c,t-1}$	26.686	28.622	26.527	0.000
	(0.000)	(0.000)	(0.000)	
$Log\ (Pat_{i,t-1}+1)$	10.190	83.372	4.204	0.000
	(0.000)	(0.000)	(0.000)	
$Log\ (Pat_{i,t-1}+1)^2$	18.546	161.610	6.845	0.000
	(0.000)	(0.000)	(0.000)	
$Sa_{i,t-1}$	253.864	165.297	261.108	0.000
	(154.808)	(113.442)	(159.574)	
$Cf_{i,t-1}$	13.40	10.987	13.600	0.000
	(6.890)	(6.981)	(6.881)	
$Dbt_{i,t-1}$	0.244	0.426	0.229	0.000
	(0.000)	(0.000)	(0.000)	
Other related variables				
Real total assets	164.226	729.123	118.023	0.000
	(25.892)	(95.587)	(23.621)	
Age	10.871	13.040	10.693	0.000
	(9.000)	(10.000)	(8.000)	
Political affiliation	80.502	78.104	80.698	0.000
	(90.000)	(90.000)	(90.000)	
Percentage of state shares	4.205	4.802	4.156	0.000
	(0.000)	(0.000)	(0.000)	
Region	1.334	1.290	1.338	0.000
	(1.000)	(1.000)	(1.000)	
Observations	1,651,881	124,895	1,526,986	

Notes: All main regression variables and percentage of state shares are shown in percentage terms. Real total assets are expressed in millions of CNY. All monetary variables are deflated using provincial PPI. The last column shows the p-values associated with the mean-equality test between the group of firms with patent applications and the group of firms without patent applications (*Diff*). Complete definitions of all the variables and classification standards are shown in Appendix D.

Table 4.3
Modified baseline Euler equation (4.1) for the full sample

	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Probability	Probability	Truncated	Truncated	Truncated	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.150***	1.038***	0.959***	3.535***	3.191***	2.948***	1.862***	1.680***	1.552***
	[0.049]	[0.047]	[0.119]	[0.150]	[0.143]	[0.366]	[0.079]	[0.075]	[0.193]
$PT_{i,c,t-1}$	0.092**	0.106***	0.073*	0.282**	0.326***	0.225*	0.148**	0.172***	0.118*
	[0.039]	[0.039]	[0.039]	[0.120]	[0.120]	[0.120]	[0.063]	[0.063]	[0.063]
$Log\ (Pat_{i,t-1}+1)$	15.790***	15.791***	15.846***	48.528***	48.534***	48.704***	25.560***	25.562***	25.648***
	[0.097]	[0.097]	[0.097]	[0.280]	[0.281]	[0.281]	[0.154]	[0.154]	[0.154]
$Log\ (Pat_{i,t-1}+1)^2$	-3.390***	-3.389***	-3.403***	-10.418***	-10.415***	-10.458***	-5.487***	-5.486***	-5.507***
	[0.042]	[0.042]	[0.042]	[0.128]	[0.128]	[0.129]	[0.068]	[0.068]	[0.068]
$Sa_{i,t-1}$	-0.759***	-0.761***	-0.772***	-2.334***	-2.339***	-2.372***	-1.229***	-1.232***	-1.249***
	[0.014]	[0.014]	[0.014]	[0.043]	[0.043]	[0.043]	[0.023]	[0.023]	[0.023]
$Cf_{i,t-1}$	2.777***	2.778***	2.666***	8.534***	8.539***	8.194***	4.495***	4.498***	4.315***
	[0.134]	[0.134]	[0.135]	[0.411]	[0.411]	[0.412]	[0.217]	[0.217]	[0.218]
$Dbt_{i,t-1}$	1.211***	1.206***	1.170***	3.722***	3.706***	3.596***	1.961***	1.952***	1.894***
	[0.224]	[0.224]	[0.224]	[0.689]	[0.689]	[0.687]	[0.363]	[0.363]	[0.362]
Prob $>$ F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.223	0.223	0.222	0.223	0.223	0.222	0.223	0.223	0.222
Firms	440,383	440,383	440,382	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972
Uncensored	124,895	124,895	124,890	124,895	124,895	124,890	124,895	124,895	124,890

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equation (4.1) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry, and location dummies are included in all specifications but not reported. Prob $>$ F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.4
Modified baseline Euler equation (4.2) for the full sample

	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability	Probability	Probability	Truncated	Truncated	Truncated	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.151***	1.031***	0.922***	3.541***	3.173***	2.841***	1.859***	1.666***	1.480***
	[0.049]	[0.047]	[0.117]	[0.151]	[0.143]	[0.360]	[0.079]	[0.075]	[0.190]
$PT_{i,c,t-1}$	0.085**	0.096**	0.068*	0.315***	0.346***	0.222*	0.111*	0.127**	0.105*
	[0.039]	[0.039]	[0.039]	[0.120]	[0.120]	[0.120]	[0.064]	[0.064]	[0.064]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$	-0.283***	-0.236***	-0.748***	-0.892***	-0.747***	-2.307***	-0.460***	-0.384***	-1.210***
	[0.067]	[0.051]	[0.186]	[0.208]	[0.156]	[0.569]	[0.110]	[0.083]	[0.301]
$Log\ (Pat_{i,t-1} + 1)$	15.788***	15.790***	15.847***	48.522***	48.531***	48.704***	25.557***	25.560***	25.649***
	[0.097]	[0.097]	[0.097]	[0.280]	[0.281]	[0.280]	[0.154]	[0.154]	[0.154]
$Log\ (Pat_{i,t-1} + 1)^2$	-3.389***	-3.389***	-3.403***	-10.416***	-10.415***	-10.459***	-5.486***	-5.485***	-5.508***
	[0.042]	[0.042]	[0.042]	[0.128]	[0.128]	[0.129]	[0.068]	[0.068]	[0.068]
$Sa_{i,t-1}$	-0.759***	-0.761***	-0.772***	-2.333***	-2.338***	-2.372***	-1.229***	-1.231***	-1.249***
	[0.014]	[0.014]	[0.014]	[0.043]	[0.043]	[0.043]	[0.023]	[0.023]	[0.023]
$Cf_{i,t-1}$	2.780***	2.781***	2.666***	8.545***	8.546***	8.192***	4.501***	4.501***	4.314***
	[0.134]	[0.134]	[0.135]	[0.410]	[0.411]	[0.412]	[0.217]	[0.217]	[0.218]
$Dbt_{i,t-1}$	1.211***	1.204***	1.166***	3.721***	3.702***	3.584***	1.960***	1.950***	1.887***
	[0.224]	[0.224]	[0.224]	[0.690]	[0.690]	[0.687]	[0.363]	[0.363]	[0.362]
Prob $>$ F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.223	0.223	0.222	0.223	0.223	0.222	0.223	0.223	0.222
Firms	440,383	440,383	440,382	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972
Uncensored	124,895	124,895	124,890	124,895	124,895	124,890	124,895	124,895	124,890

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equation (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry, and location dummies are included in all specifications but not reported. Prob $>$ F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.5

Modified baseline Euler equations (4.1) and (4.2) of IV Tobit estimation for the full sample

	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
.	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.952***	0.859***	0.356**	1.950***	0.842***	0.320**
	[0.258]	[0.048]	[0.129]	[0.256]	[0.048]	[0.128]
$PT_{i,c,t-1}$	0.068**	0.085**	0.066*	0.060**	0.096**	0.064*
	[0.031]	[0.038]	[0.033]	[0.030]	[0.039]	[0.032]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.452***	-0.352***	-1.021***
				[0.075]	[0.068]	[0.268]
$Log\ (Pat_{i,t-1} + 1)$	18.913***	18.954***	18.959***	18.910***	18.978***	18.958***
	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]
$Log\ (Pat_{i,t-1} + 1)^2$	-2.123***	-2.135***	-2.168***	-2.122***	-2.134***	-2.167***
	[0.101]	[0.101]	[0.101]	[0.101]	[0.101]	[0.101]
$Sa_{i,t-1}$	-1.312***	-1.315***	-1.335***	-1.311***	-1.315***	-1.334***
	[0.045]	[0.045]	[0.045]	[0.045]	[0.045]	[0.045]
$Cf_{i,t-1}$	5.053***	5.055***	5.049***	5.054***	5.056***	5.048***
	[0.310]	[0.310]	[0.310]	[0.310]	[0.310]	[0.310]
$Dbt_{i,t-1}$	1.926***	1.923***	1.902***	1.928***	1.922***	1.895***
	[0.359]	[0.359]	[0.358]	[0.359]	[0.359]	[0.357]
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Wald test of exogeneity (p−value)	0.000	0.000	0.000	0.000	0.000	0.000
Anderson−Rubin (p−value)	0.000	0.000	0.000	0.000	0.000	0.000
Firms	408,809	408,809	408,809	408,809	408,809	408,809
Observations	1,509,647	1,509,647	1,509,647	1,509,647	1,509,647	1,509,647
Left-censored	1,399,056	1,399,056	1,399,056	1,399,056	1,399,056	1,399,056
Uncensored	110,591	110,591	110,591	110,591	110,591	110,591

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equations (4.1) and (4.2) using the IV Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm has patent applications (uncensored observations), and zero otherwise (left-censored observations). Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Wald test of exogeneity is distributed as chi-square under the null hypothesis of exogeneity. Anderson-Rubin is under the null hypothesis that the minimum canonical correlation is zero. Complete definitions of all variables are shown in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.6
Modified baseline Euler equations (4.1) and (4.2) for the full sample with alternative measures of financial development and political turnover

	Panel A: an alternative measure of FD based on municipal districts					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	0.855***	0.915***	0.046	0.848***	0.906***	0.029
	[0.064]	[0.064]	[0.163]	[0.064]	[0.064]	[0.163]
$PT_{i,c,t-1}$	0.129**	0.137**	0.129**	0.129**	0.110*	0.130**
	[0.064]	[0.063]	[0.063]	[0.064]	[0.064]	[0.064]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.088	-0.309***	-0.796***
				[0.107]	[0.083]	[0.250]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.223	0.223	0.222	0.223	0.223	0.222
Firms	439,134	439,134	439,120	439,134	439,134	439,120
Observations	1,647,580	1,647,580	1,647,120	1,647,580	1,647,580	1,647,120
Left-censored	1,523,175	1,523,175	1,522,733	1,523,175	1,523,175	1,522,733
Uncensored	124,405	124,405	124,387	124,405	124,405	124,387
	Panel B: an alternative measure of political turnover in calendar years					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.878***	1.694***	1.564***	1.874***	1.692***	1.508***
	[0.079]	[0.075]	[0.193]	[0.079]	[0.076]	[0.194]
$PT_{i,c,t-1}$	0.244***	0.244***	0.136**	0.213***	0.242***	0.127*
	[0.065]	[0.065]	[0.065]	[0.066]	[0.066]	[0.065]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.320***	0.242	-0.656**
				[0.118]	[0.066]	[0.338]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.223	0.223	0.222	0.223	0.223	0.222
Firms	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972
Uncensored	124,895	124,895	124,890	124,895	124,895	124,890
	Panel C: an alternative measure of political turnover without tenures of five years					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.866***	1.682***	1.557***	1.869***	1.687***	1.536***
	[0.079]	[0.075]	[0.193]	[0.079]	[0.076]	[0.193]
$PT_{i,c,t-1}$	0.186**	0.191***	0.114	0.167**	0.211***	0.112
	[0.073]	[0.073]	[0.073]	[0.074]	[0.075]	[0.073]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.225*	0.186	-0.422*
				[0.128]	[0.112]	[0.241]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.223	0.223	0.222	0.223	0.223	0.222
Firms	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,526,986	1,526,986	1,526,972	1,526,986	1,526,986	1,526,972
Uncensored	124,895	124,895	124,890	124,895	124,895	124,890

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equations (4.1) and (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.7
Modified baseline Euler equations (4.1) and (4.2) for the full sample with alternative measures of innovation activities

	Panel A: innovation is measured by the number of invention patent applications					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	0.693***	0.615***	0.244**	0.694***	0.606***	0.206**
	[0.039]	[0.038]	[0.109]	[0.039]	[0.038]	[0.104]
$PT_{i,c,t-1}$	0.064**	0.074**	0.056*	0.050	0.052	0.049
	[0.031]	[0.031]	[0.031]	[0.032]	[0.032]	[0.032]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.185***	-0.193***	-0.809***
				[0.054]	[0.041]	[0.152]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.235	0.235	0.235	0.235	0.235	0.235
Firms	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,584,463	1,584,463	1,584,448	1,584,463	1,584,463	1,584,448
Uncensored	67,418	67,418	67,414	67,418	67,418	67,414
	Panel B: innovation is measured by the number of patents applied by individuals					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.819***	1.643***	1.558***	1.816***	1.630***	1.488***
	[0.078]	[0.074]	[0.190]	[0.078]	[0.074]	[0.187]
$PT_{i,c,t-1}$	0.163***	0.186***	0.133**	0.132**	0.148**	0.121*
	[0.062]	[0.062]	[0.062]	[0.063]	[0.063]	[0.063]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.395***	-0.333***	-1.142***
				[0.109]	[0.083]	[0.298]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.220	0.220	0.219	0.220	0.220	0.219
Firms	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,532,489	1,532,489	1,532,473	1,532,489	1,532,489	1,532,473
Uncensored	119,392	119,392	119,389	119,392	119,392	119,389
	Panel C: innovation is measured by the number of patents granted					
	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	1.518***	1.331***	1.314***	1.517***	1.320***	1.242***
	[0.064]	[0.061]	[0.154]	[0.065]	[0.061]	[0.152]
$PT_{i,c,t-1}$	0.097*	0.116**	0.074	0.071	0.087	0.062
	[0.052]	[0.052]	[0.052]	[0.053]	[0.053]	[0.052]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.319***	-0.257***	-1.110***
				[0.091]	[0.070]	[0.249]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.248	0.248	0.247	0.248	0.248	0.247
Firms	440,383	440,383	440,382	440,383	440,383	440,382
Observations	1,651,881	1,651,881	1,651,862	1,651,881	1,651,881	1,651,862
Left-censored	1,537,965	1,537,965	1,537,947	1,537,965	1,537,965	1,537,947
Uncensored	113,916	113,916	113,915	113,916	113,916	113,915

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equations (4.1) and (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm i has patent applications/granted (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.8
Modified augmented Euler equations (4.1) and (4.2) for the full sample with contemporaneous terms

	Credit ratio	*Deposit ratio*	*Saving ratio*	*Credit ratio*	*Deposit ratio*	*Saving ratio*
	(1)	(2)	(3)	(4)	(5)	(6)
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t}$	0.366**	0.360**	0.113	0.264	0.440***	0.337
	[0.170]	[0.161]	[0.283]	[0.175]	[0.160]	[0.278]
$FinDev_{i,c,t-1}$	1.473***	1.302***	1.489***	1.572***	1.225***	1.272***
	[0.166]	[0.152]	[0.235]	[0.171]	[0.151]	[0.232]
SUM ($FinDev_{i,c,t}$ and $FinDev_{i,c,t-1}$)	1.839***	1.663***	1.602***	1.837***	1.665***	1.609***
	[0.084]	[0.081]	[0.235]	[0.084]	[0.081]	[0.234]
$PT_{i,c,t}$	0.109	0.121*	-0.003	0.134**	0.148**	-0.003
	[0.066]	[0.066]	[0.066]	[0.067]	[0.067]	[0.066]
$PT_{i,c,t-1}$	0.179***	0.205***	0.114**	0.150**	0.165**	0.099
	[0.065]	[0.065]	[0.065]	[0.066]	[0.066]	[0.065]
SUM ($PT_{i,c,t}$ and $PT_{i,c,t-1}$)	0.288***	0.326***	0.112	0.284***	0.312***	0.096
	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]
$FinDev_{i,c,t} * PT_{i,c,t}$				0.192	0.115	0.108
				[0.115]	[0.090]	[0.334]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$				-0.358***	-0.357***	-1.133***
				[0.113]	[0.086]	[0.315]
$Log\ (Pat_{i,t-1}+1)$	25.473***	25.473***	25.556***	25.470***	25.471***	25.556***
	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]	[0.155]
$Log\ (Pat_{i,t-1}+1)^2$	-5.464***	-5.461***	-5.482***	-5.463***	-5.461***	-5.482***
	[0.069]	[0.069]	[0.069]	[0.069]	[0.069]	[0.069]
$Sa_{i,t}$	-0.804***	-0.806***	-0.820***	-0.804***	-0.806***	-0.820***
	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]	[0.027]
$Sa_{i,t-1}$	-0.632***	-0.632***	-0.636***	-0.631***	-0.632***	-0.636***
	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]	[0.026]
$Cf_{i,t}$	3.402***	3.403***	3.245***	3.415***	3.422***	3.256***
	[0.252]	[0.252]	[0.253]	[0.252]	[0.252]	[0.253]
$Cf_{i,t-1}$	2.776***	2.783***	2.708***	2.773***	2.778***	2.702***
	[0.259]	[0.260]	[0.260]	[0.259]	[0.260]	[0.260]
$Dbt_{i,t}$	3.063***	3.059***	2.984***	3.056***	3.052***	2.983***
	[0.358]	[0.358]	[0.357]	[0.358]	[0.358]	[0.357]
$Dbt_{i,t-1}$	2.832***	2.825***	2.757***	2.827***	2.819***	2.749***
	[0.380]	[0.380]	[0.378]	[0.380]	[0.380]	[0.378]
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.224	0.224	0.224	0.224	0.224	0.224
Firms	436,173	436,173	436,161	436,173	436,173	436,161
Observations	1,632,507	1,632,507	1,632,462	1,632,507	1,632,507	1,632,462
Left-censored	1,508,656	1,508,656	1,508,617	1,508,656	1,508,656	1,508,617
Uncensored	123,851	123,851	123,845	123,851	123,851	123,845

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equations (4.1) and (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). SUM ($FinDev_{i,c,t}$ and $FinDev_{i,c,t-1}$) is the sum of the marginal effects of the contemporaneous financial development variable, $FinDev_{i,c,t}$, and the lagged financial development variable, $FinDev_{i,c,t-1}$. SUM ($PT_{i,c,t}$ and $PT_{i,c,t-1}$) is the sum of the marginal effects of the contemporaneous political turnover variable, $PT_{i,c,t}$, and the lagged political turnover variable, $PT_{i,c,t-1}$. The marginal effect associated with the $FinDev_{i,c,t} * PT_{i,c,t}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t}$ evaluated at 0 and 1 of $PT_{i,c,t}$. The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry, and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.9
Modified baseline Euler equations (4.1) and (4.2) of more robustness tests

	Drop firms with sales less than 20 million CNY		Drop firms not located in prefecture-level cities		Drop firms in years 2003, 2008 and 2013		Adding Short-term debts		Zero-inflated Poisson		Probit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1}$	2.014***	2.009***	1.765***	1.762***	1.827***	1.816***	1.873***	1.870***	5.933***	5.906***	1.167***	1.169***
	[0.098]	[0.099]	[0.079]	[0.079]	[0.087]	[0.087]	[0.079]	[0.079]	[0.319]	[0.320]	[0.049]	[0.049]
$PT_{i,c,t-1}$	0.159**	0.115	0.245***	0.232***	0.214***	0.180**	0.149**	0.111*	1.094***	1.085***	0.069*	0.058
	[0.079]	[0.080]	[0.065]	[0.067]	[0.074]	[0.075]	[0.063]	[0.064]	[0.275]	[0.278]	[0.040]	[0.040]
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$		-0.543***		-0.149*		-0.482***		-0.467***		-1.050**		-0.302***
		[0.138]		[0.075]		[0.126]		[0.110]		[0.492]		[0.070]
$Log\ (Pat_{i,t-1}+1)$	29.360***	29.357***	24.947***	24.946***	24.481***	24.458***	25.541***	25.538***	23.214***	23.212***	15.644***	15.642***
	[0.185]	[0.185]	[0.160]	[0.160]	[0.172]	[0.172]	[0.154]	[0.154]	[0.139]	[0.139]	[0.056]	[0.056]
$Log\ (Pat_{i,t-1}+1)^2$	-6.163***	-6.162***	-5.499***	-5.498***	-5.308***	-5.304***	-5.485***	-5.484***	-1.278***	-1.278***		
	[0.082]	[0.082]	[0.071]	[0.071]	[0.077]	[0.077]	[0.068]	[0.068]	[0.011]	[0.011]		
$Sa_{i,t-1}$	-1.500***	-1.499***	-1.166***	-1.166***	-1.179***	-1.156***	-1.209***	-1.208***	-5.834***	-5.831***	-0.745***	-0.745***
	[0.028]	[0.028]	[0.023]	[0.023]	[0.026]	[0.026]	[0.023]	[0.023]	[0.117]	[0.117]	[0.014]	[0.014]
$Cf_{i,t-1}$	4.626***	4.633***	3.836***	3.838***	4.727***	4.853***	4.612***	4.618***	25.067***	25.070***	2.722***	2.726***
	[0.266]	[0.266]	[0.221]	[0.221]	[0.249]	[0.249]	[0.217]	[0.217]	[0.990]	[0.990]	[0.132]	[0.132]
$Dbt_{i,t-1}$	2.005***	2.004***	1.687***	1.686***	2.263***	3.014***	2.781***	2.781***	9.627***	9.606***	1.207***	1.207***
	[0.451]	[0.451]	[0.367]	[0.367]	[0.401]	[0.408]	[0.369]	[0.369]	[1.653]	[1.653]	[0.227]	[0.227]
$ShortDbt_{i,t-1}$							2.201***	2.203***				
							[0.117]	[0.117]				
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.213	0.213	0.223	0.223	0.222	0.222	0.223	0.223	0.358	0.358	0.301	0.3011
Firms	363,110	363,110	400,591	400,591	381,729	381,727	440,379	440,379	440,383	440,383	440,383	440,383
Observations	1,312,747	1,312,747	1,490,899	1,490,899	1,216,287	1,216,287	1,651,874	1,651,874	1,651,881	1,651,881	1,651,881	1,651,881
Left-censored	1,193,371	1,193,371	1,383,443	1,383,443	1,130,509	1,130,509	1,526,980	1,526,980	/	/	/	/
Uncensored	119,376	119,376	107,456	107,456	85,778	85,778	124,894	124,894	/	/	/	/

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equations (4.1) and (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t}+1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Year, ownership, industry and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Table 4.10
Modified baseline Euler equation (4.2) of further tests

	Panel A: Turnover types					
	Predicted turnover years		Predicted turnover ages		Tenure lengths	
	(1) Around 5th	(2) Not around 5th	(3) Around 55	(4) Not around 55	(3) Short	(4) Long
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$	-0.062	-0.392**	0.291	-0.701***	-0.743***	0.170
	[0.183]	[0.171]	[0.222]	[0.133]	[0.221]	[0.163]
Diff(p-value)	(0.000)***		(0.000)***		(0.000)***	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.217	0.226	0.223	0.223	0.226	0.218
Firms	300,300	383,409	247,847	392,922	362,948	321,339
Observations	548,079	1,098,591	480,081	1,169,465	980,358	666,312
Left-censored	506,523	1,015,504	441,426	1,083,275	909,629	612,398
Uncensored	41,556	83,087	38,655	86,190	70,729	53,914
	Panel B: Firms' political connection					
	Ownership		Political affiliation		State shares	
	(1) Non-SOEs	(2) SOEs	(3) Without	(4) With	(5) Without	(6) With
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$	-0.343***	-0.925**	-0.402***	-0.497***	-0.319***	-0.845**
	[0.116]	[0.385]	[0.140]	[0.181]	[0.117]	[0.374]
Diff(p-value)	(0.000)***		(0.000)***		(0.000)***	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.223	0.279	0.218	0.248	0.222	0.270
Firms	425,982	23,415	370,374	140,207	423,355	30,827
Observations	1,535,703	68,191	1,251,360	400,521	1,513,187	90,700
Left-censored	1,420,150	62,654	1,157,207	369,779	1,400,371	82,426
Uncensored	115,553	5,537	94,153	30,742	112,816	8,274
	Panel C: Firms' financial constraints					
	Size		Age		SA index	
	(3) Small	(4) Large	(5) Young	(6) Mature	(11) Low	(12) High
	Censored	Censored	Censored	Censored	Censored	Censored
$FinDev_{i,c,t-1} * PT_{i,c,t-1}$	-0.336***	-0.412**	-0.333**	-0.538***	-0.504***	-0.254**
	[0.119]	[0.172]	[0.153]	[0.161]	[0.168]	[0.125]
Diff(p-value)	(0.000)***		(0.000)***		(0.000)***	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.202	0.214	0.215	0.227	0.215	0.204
Firms	269,690	268,719	315,376	239,158	264,808	274,107
Observations	694,414	957,341	781,303	870,280	972,799	679,010
Left-censored	671,079	855,793	731,761	794,997	871,706	655,212
Uncensored	23,335	101,548	49,542	75,283	101,093	23,798

Notes: This table reports the average marginal effects in the percentage of the modified baseline Euler equation (4.2) using the Pooled Tobit. The dependent variable $Log\ (Pat_{i,t} + 1)$ is a censored variable that takes its real value if the firm i has patent applications (uncensored observations), and zero otherwise (left-censored observations). The marginal effect associated with the $FinDev_{i,c,t-1} * PT_{i,c,t-1}$ interaction is computed based on the difference of the average marginal effects relative to $FinDev_{i,c,t-1}$ evaluated at 0 and 1 of $PT_{i,c,t-1}$. Heteroscedasticity-consistent standard errors are reported in parentheses. Diff (p-value) is the p-value for the difference of the marginal effects of the interaction term between two comparative groups. Year, ownership, industry, and location dummies are included in all specifications but not reported. Prob > F is the test of joint significance for parameters and the null hypothesis is that all the regression coefficients are simultaneously equal to zero. Pseudo R^2 is McFadden's pseudo-R-squared in the Pooled Tobit regressions. Complete definitions of all variables are in Appendix D. Significance at the 1%, 5%, and 10% level is indicated by ***, ** and * respectively.

Appendix

Appendix A. NBS firm-level data

To check the data reliability, we compare the numbers of enterprises each year recorded in the NBS firm-level data with those in the *China Statistical Yearbook*. The results are reported in Table 4.A1. The statistics for all years before 2008 in the dataset are identical with those in the *China Statistical Yearbook*, verifying the data used in the study are also the basis of the statistics in the *China Statistical Yearbook*. The statistics starting from the year 2008 are less than those in the *China Statistical Yearbook*, while the discrepancies are acceptable. However, we drop the observations starting from the year 2008 to estimate again to enhance robustness. The estimation results keep qualitatively unchanged and the robustness method can avoid the influence of the financial crisis starting from the year 2007 on firms' behaviours. Since the data in the year 2010 lose too many variables, we do not cover the data in the year 2010 in the study to secure data quality and assume the year 2009 and the year 2011 as two consecutive years. We also find that the number of enterprises has uninterrupted growth before the year 2011 while decreases afterwards. The decrease is caused by the revision of the standard of the 'above-scale' enterprises in the year 2011, which raises the threshold for inclusion of the 'above-scale' from five million CNY to twenty million CNY.

Table 4.A1

Comparison of the NBS firm-level data with the *China Statistical Yearbook*

Year	NBS firm-level data	*China Statistical Yearbook*
2003	196,222	196,222
2004	276,474	276,474
2005	271,835	271,835
2006	301,961	301,961
2007	336,768	336,768
2008	412,165	426,113
2009	434,682	434,364
2011	302,593	325,609
2012	324,604	343,769
2013	344,875	369,813
2014	309,052	377,888
Total	3,511,231	3,660,816

We process the NBS-firm level data by following the next steps. First, since we use the legal person code (*fa ren dai ma*) to construct a panel, we adjust firms' legal person codes. We supplement some observations' legal person codes to nine digits and capitalize all English letters in some observations' legal person codes which include lower case letters.[169] Since some observations in the years 2008 and 2009 do not record legal person codes and firms' names, we use the information in other years to retrieve them. We then remove the observations whose legal person codes are missing or duplicated since these observations could not be used to construct a panel. Second, we update all industry codes in the dataset to keep consistent with the revision of the 'National Industries Classification' in 2012 and then remove the observations in the industries transferred from or disappeared in manufacturing sectors. Third, we do not cover some observations to eliminate potential errors caused by misreporting or mismeasurement of accounting data. Specifically, we drop the observations in the year 2010 since too many variables in that year are missing, and then treat the years 2009 and 2011 as two consecutive years. We next delete the observations without annual sales of more than 5 million CNY to avoid the influence of non-'above scale' enterprises. We finally exclude the observations which do not follow the basic rules of the Generally Accepted Accounting Principles (GAAP), including the observations whose total fixed assets are greater than total assets; liquid assets are greater than total assets; current depreciation is greater than accumulated depreciation. After the above adjustments, the dataset includes 3,215,479 observations. Table 4.A2 shows the detailed distribution of observations in the dataset.

[169] According to the regulations of the General Administration of Quality Supervision (AQSIQ), the legal person codes of Chinese firms must be nine digits and Arabic numerals or uppercase English letters.

Table 4.A2

Distribution of firm-level observations by years

Year	Number of observations	Per cent (%)	Cumulative (%)
2003	172,374	5.36	5.36
2004	261,491	8.13	13.49
2005	258,347	8.03	21.53
2006	289,931	9.02	30.54
2007	329,586	10.25	40.79
2008	404,212	12.57	53.37
2009	316,911	9.86	63.22
2010	/	/	/
2011	302,386	9.40	72.62
2012	323,822	10.07	82.70
2013	343,194	10.67	93.37
2014	213,224	6.63	100.00
Total	3,215,478	100.00	

Number of years per firm	Number of observations	Per cent (%)	Cumulative (%)
1	153,433	4.77	4.77
2	235,384	7.32	12.09
3	323,019	10.05	22.14
4	307,468	9.56	31.70
5	315,095	9.80	41.50
6	389,658	12.12	53.62
7	341,852	10.63	64.25
8	216,416	6.73	70.98
9	279,000	8.68	79.66
10	372,850	11.60	91.25
11	281,303	8.75	100.00
Total	3,215,478	100.00	

Appendix B. Detailed information on the sample cities

According to China's constitution, there are three administration levels of cities in China: province-level, prefecture-level, and county-level. Municipalities are the first-level (province-level) administrative divisions which are directly governed by the central government and administratively equivalent to the other 30 provinces, autonomous regions, and special administrative regions (including Hong Kong, Macao, and Taiwan). Sub-provincial cities and ordinary prefecture-level cities are the secondary-level (prefecture-level) administrative divisions and directly governed by the provincial governments. Prefecture-level cities are ranked below province-level cities while above county-level cities in China, and occupy 88% of all prefecture-level administrative divisions. The difference between sub-provincial cities and ordinary prefecture-level cities is that sub-provincial cities are a half level higher than ordinary prefecture-level cities. County-level cities are the third-level (county-level) administrative divisions and governed by the prefecture-level governments. Only a very small number of county-level cities are independently organized outside prefecture-level administrative divisions and directly governed by the provincial governments. County-level cities are the lowest-ranking cities in China. With the rapid development of urbanization during the last decades in China, more prefecture-level administrative divisions (including areas, autonomous prefectures) and county-level administrative divisions (including counties, autonomous counties) become prefecture-level cities and county-level cities. Thus, the number of cities in China increases steadily each year.

At the end of 2014, there are 4 municipalities, 15 sub-provincial cities, 273 prefecture-level cities, and 361 county-level cities in China. Our sample includes all 4 municipalities, 15 sub-provincial cities, 273 prefecture-level cities, and 15 county-level cities directly governed by provincial governments. The four municipalities are Beijing, Tianjin, Shanghai, and

Chongqing, which are all metropolises with a developed economy and huge population. The 15 sub-provincial cities include 10 provincial capital cities and 5 cities with independent planning status, which are Shenyang, Dalian, Changchun, Harbin, Nanjing, Hangzhou, Ningbo, Xiamen, Jinan, Qingdao, Wuhan, Guangzhou, Shenzhen, Chengdu, and Xi'an. The 15 county-level cities directly governed by provincial governments are Jiyuan in Henan Province, Xiantao, Qianjiang, and Tianmen in Hubei Province, Danzhou, Wuzhishan, Qionghai, Wenchang, Wanning and Dongfang in Hainan Province, Shihezi, Aral, Tumxuk, Wujiaqu, and Beitun in Xinjiang Uygur Autonomous Region. Table 4.A3 shows the distribution of the sampled cities by provincial administrative areas and Table 4.A4 presents the distribution of the sampled cities by years. Fig. 4.A1 is the map presenting the distribution of the sampled cities in China.

Table 4.A3
Distribution of the sample cities by provincial administrative areas

Provincial administrative areas	Grouped by administrative levels				Provincial total
	Municipality (directly governed by the central government)	Prefecture-level city (directly governed by the provincial government)		County-level city (directly governed by the provincial government)	
		Sub-provincial city	Ordinary prefecture-level city		
Beijing	1				1
Tianjin	1				1
Hebei			11		11
Shanxi			11		11
Inner Mongolia			9		9
Liaoning		2	12		14
Jilin		1	7		8
Heilongjiang		1	11		12
Shanghai	1				1
Jiangsu		1	12		13
Zhejiang		2	9		11
Anhui			17		17
Fujian		1	8		9
Jiangxi			11		11
Shandong		2	15		17
Henan			17	1	18
Hubei		1	11	3	15
Hunan			13		13
Guangdong		2	19		21
Guangxi			14		14
Hainan			3	6	9
Chongqing	1				1
Sichuan		1	17		18
Guizhou			6		6
Yunnan			8		8
Tibet			1		1
Shaanxi		1	9		10
Gansu			12		12
Qinghai			2		2
Ningxia			5		5
Xinjiang			2	5	7
National total	4	15	272	15	306

Table 4.A4
Distribution of the sample cities by years

Year	Grouped by administrative levels				Total
	Municipality (directly governed by the central government)	Prefecture-level city (directly governed by the provincial government)		County-level city (directly governed by the provincial government)	
		Sub-provincial city	Ordinary prefecture-level city		
2003	4	15	265		284
2004	4	15	267		286
2005	4	15	267		286
2006	4	15	267		286
2007	4	15	268		287
2008	4	15	268		287
2009	4	15	268		287
2010	4	15	268		287
2011	4	15	269	14	302
2012	4	15	270	15	304
2013	4	15	271	15	305
2014	4	15	271	15	305
Total	4	15	271	15	305

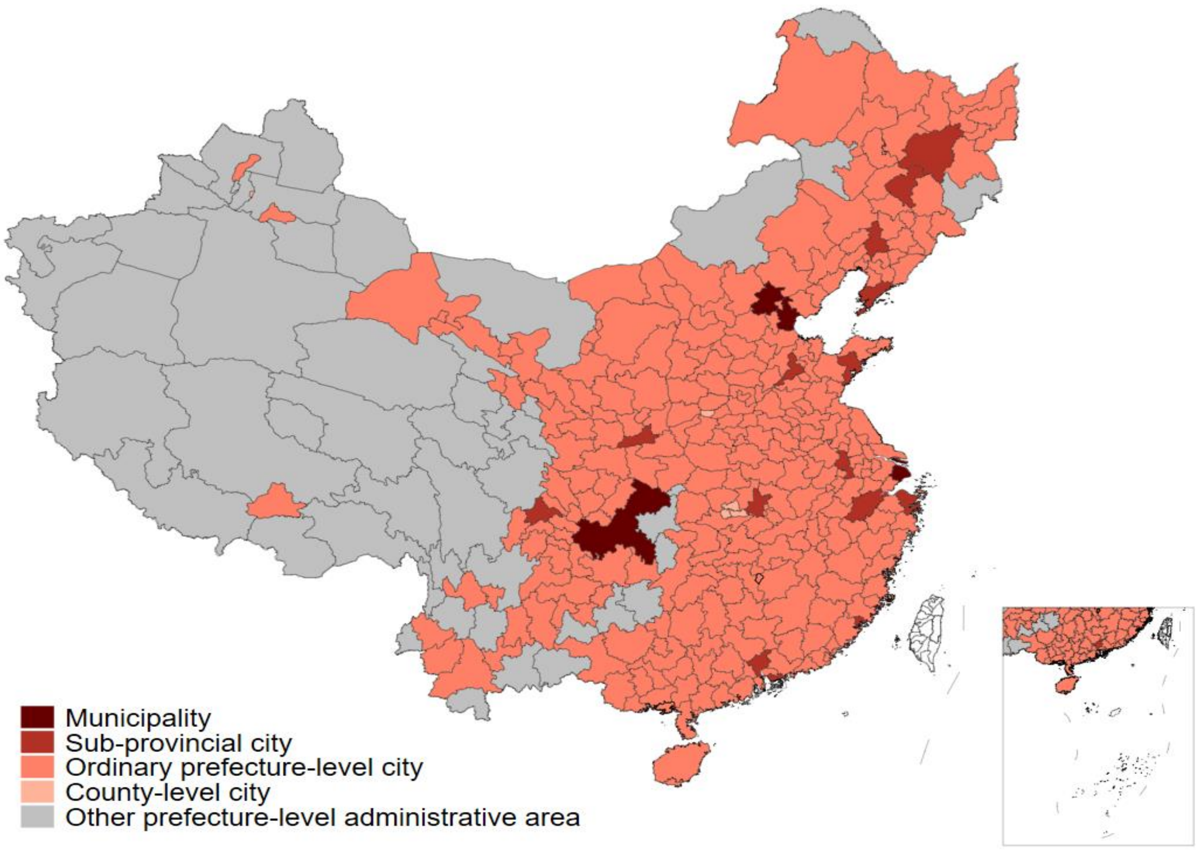


Figure 4.A1. Distribution of the sample cities in China

Appendix C. Distribution of turnovers of city party secretary by provinces and years

Table 4.A5

Distribution of the number of political turnovers by provincial administrative areas and years over the period 2003 to 2014

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
Beijing	1										1		2
Tianjin					1						1		2
Hebei	5	2	2	1	7	5	4	2	2	4	6	2	42
Shanxi	4		2	9	2	6	3		5	5	3	1	40
Inner Mongolia	8		5		5	4	1	4	7	4	1	4	43
Liaoning	4	4	4	6	1	6	1	2	7	3	5	3	46
Jilin	4		4	1	5	3	1	1	5	1	2		27
Heilongjiang	4	6	5	1	2	6	1	5	7	2	1	2	42
Shanghai	1				1	1					1		4
Jiangsu	7		4	2		4	1	2	4	5	4	2	35
Zhejiang	3	4	3	1	1	6	1	1	4	3	7	2	36
Anhui	8	1	3	3		10	3	2	1	5	9	2	47
Fujian	1	2	6		2	4	1		1	4	4	1	26
Jiangxi	4	2	2	2	4	4	2	1	2	5	1	5	34
Shandong	8	1		2	10	5			5	8	5	2	46
Henan	7	5		3	7	7			11	6	9	1	56
Hubei	12	1	3	5	7	6	4	3	3	4	13		61
Hunan	5	2		3	5	8	2	1	1	4	10	1	42
Guangdong	8	5	3	5	8	6	1	4	6	12	5	1	64
Guangxi	6	1	1	1	4	10	4	3		5	8	3	46
Hainan	4	1	5	1	6	5	2	4	5	5	5	3	46
Chongqing	1			1		1				1	1		5
Sichuan	6	6	7	8	4	7	3	1	4	9	4	2	61
Guizhou	5		1		4	5	1		2	1	7	2	28
Yunnan	8	2	4	1	5	6		4	2	4	10	2	48
Tibet	5			1	3	3			3	3	1	1	20
Shaanxi	6	2	2	3	2	5		1	3	3	4	3	34
Gansu	2	2	6	4	1	10	3	2		8	4	3	45
Qinghai	2	1	3		3	3		1	3	1	4	1	22
Ningxia	2	3			1	3			3	1	1		14
Xinjiang	2	4	8	5	3	5	2	2	1	11	7	4	54
National total	143	57	83	69	104	154	41	46	97	127	144	53	1,118

Chapter 4
To what extent does political turnover affect the finance-innovation nexus: Evidence from China

Appendix D. Variable definitions and classification standards

Log (Pat + 1): natural logarithm of the number of a firm's patent applications plus one

Credit ratio: the ratio of overall loans in a city's financial system (including both banking institutions and non-banking financial institutions) to the city's gross regional product (GRP).

Deposit ratio: the ratio of overall deposits in a city's financial system to the city's GRP.

Saving ratio: the ratio of overall household savings in the city's financial system to the city's GRP.

Political turnover: the change of city party secretary.

Sales: firms' total sales including domestic and overseas sales.

Cash flows: firms' net income plus current depreciation.

New long-term debt issue: the difference between long-term debt in year *t* and *t-1*.

Total assets: the sum of firms' long-term assets and current assets. Long-term assets comprise fixed assets(tangible assets), intangible assets, deferred assets, long-term investments, and other long-term assets. Current assets include accounts receivable, inventories, short-term investments, and other current assets.

Real total assets: firms' Total assets are deflated using provincial ex-factory producer price indices (PPI) conducted by the NBS of China.

Age: Firms' age is calculated by the difference between accounting years and the years when firms were established.

Political affiliation: an index of a firm's political affiliation (lishu) whose categories are – 10, firms are politically affiliated at central level; 20, firms are politically affiliated at the provincial level; 40, firms are politically affiliated at the prefecture-level; 50, firms are politically affiliated at the county-level; 61, 62 and 63, firms are politically affiliated at sub-district, town or township level; 71, 72 and 73, firms are politically affiliated at community or village level; 90, firms have no political affiliation.

State shares: the percentage of paid-in capitals controlled by the State.

SA Index: An index of firms' financial constraints is from Hadlock and Pierce (2010) based on firms' size and age. The calculation method of the index is $SA = (-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$. At this equation, size is the log of real total assets. Size is replaced with a log of \$4.5 billion when firms' real total assets are converted into more than \$4.5 billion. Age is replaced with 37 years when the actual values of age exceed 37 years. The value of the SA index would increase steadily with more financial constraints.

Region: three regions are divided by the central government. – coastal (eastern) region equals 1, including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; central region equals 2, including Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hubei, and Hunan; western region equals 3, including Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 4.A6

Description of classification standards

	Turnover types	
Predicted turnover years	Around 5th Not around 5th	If a city party secretary is in the 4th, 5th, or 6th years of his term; If a city party secretary is not in the 4th, 5th, or 6th years of his term.
Predicted turnover ages	Around 55 Not around 55	If a city party secretary is 54, 55, or 56 years old during his term; If a city party secretary is not 54, 55, or 56 years old during his term;
Tenure length	Short Long	If a city party secretary has been working within 3 years; If a city party secretary has been working for more than 3 years.
	Firms' political connection	
Ownership (the majority of paid-in capitals)	SOEs Non-SOEs	At least 50% of paid-in capitals are state-owned; More than 50% of paid-in capitals are not state-owned.
Political affiliation	No With	If a firm has no political affiliation (lishu = 90); If a firm is affiliated at a level of village, community, township, town, sub-district, county, prefecture, province, and central government (lishu <90).
State Shares	No Yes	If a firm has no state shares; If a firm has some state shares.
	Firms' financial constraints	
Size	Small Large	If a firm's real total assets are in the lower quartiles (<=50%) of the distribution of real total assets of all firms in the same GB/T Two-digit industry in the same ownership type in a given year; If a firm's real total assets are in the highest quartile (>50%) of the distribution of real total assets of all firms in the same GB/T Two-digit industry in the same ownership type in a given year.
Age	Young Mature	If a firm's age is in the lower quartiles (<=50%) of all firms' age in the same GB/T Two-digit industry in the same ownership type in a given year; If a firm's age is in the highest quartile (>50%) of all firms' age in the same GB/T Two-digit industry in the same ownership type in a given year.
SA index	Low High	If a firm's SA index is in the lower half distribution (<50%) of all firms' SA indexes in the same GB/T Two-digit industry in the same ownership type in a given year; If a firm's SA index is in the highest quartiles (>=50%) of all firms' SA indexes in the same GB/T Two-digit industry in the same ownership type in a given year.

Chapter 5

Conclusions

Chapter 5
Conclusions

5.1. Summary of the main findings

The main object of the thesis is to explore China's innovation challenge from industry competition, government subsidies, and political turnover. Our study contributes to the related literature on innovation in the Chinese context by using a panel of unlisted firms collected by the NBS of China over the period from 1998 to 2014. In this section, we summarize the main findings of the thesis and put forward some policy implications related to the findings.

5.1.1. Chapter 2

In chapter 2, by employing a large panel of 555,124 industrial firms, we explore the effect of industry competition on firms' innovation activities in China over the period from 1998 to 2007. We find that no matter by which proxy of the Herfindahl-Hirschman Index (HHI), the Entropy Index (EI), the Lerner Index (LI)/Profit-Cost Margin (PCM), and the natural logarithm of the number of firms (FI), increased industry competition negatively affects firms' innovation activities measured by firms' new product output value. The finding confirms the existence of the 'Schumpeterian effect' in China. Due to the rapid impressive economic development over the past few decades, China's market is facing increasingly severe competition. This finding is important as it enables us to understand the role of industry competition on corporate innovation in China, which is complementary to the literature on innovation in the context of emerging markets.

We also find the negative effect of industry competition on firms' innovation activities is stronger in industries that are more dependent on external finance. Since firms in industries with higher EFD tend to rely more on external finance, their innovation activities are more vulnerable to higher external finance premiums caused by the increased competition. Compared to firms in industries with lower EFD which can use their internal capitals, firms in industries with higher EFD have to reduce inputs into innovation investments due to the larger pressure of external finance.

Furthermore, we find that financing constraints will tighten the negative impact of competition on innovation in industries with greater EFD. Specifically, the strengthened negative effect of increased competition is more pronounced for firms with more financial constraints, such as private firms, small firms, young firms, firms without state shares, and firms located in central and western regions. Additionally, firms with more financial constraints depend more on internal finance to innovate and show a higher sensitivity of R&D investment to cash flow. Because financially healthier firms might have better access to bank loans or other forms of external finance, the negative effect of increased competition can be alleviated to some extent.

We also make more robustness tests. First, we use the revision of the 'Catalogue of Industries to Guide Foreign Investment' in 2002 to make a quasi-natural experiment test. We make more tests to check the test validity. Second, we choose the number of application procedures that a firm has to go through to enter an industry as the instrumental variable for competition. The estimation results of the two tests successfully confirm the causal relationship between competition and innovation since high competition possibly crowds out firms' innovation activities. Third, considering potential measurement errors, we choose alternative measures of firms'' innovation activities by the number of firms' patent applications and R&D expenditure to estimate again. Fourth, to eliminate the potential omitted regression variables, we cover the contemporaneous terms of independent variables to estimate. Fifth, we take more robustness tests including dividing the domestic market, employing the Random-effects Probit estimation, selecting a long sample period from 2001 to 2016 based on aggregate industry-level data. All robustness tests keep consistent.

Last, we make some extensions. First, although some previous papers have found that there is an inverted U-shape relationship between competition and innovation in western countries (Levin et al., 1985; Aghion et al., 2005; Hashmi, 2013), we find that the inverted U-shape does not apply to the Chinese context. Second, we find that the negative effect of competition on innovation is stronger in provinces with low scores of Intellectual property rights (IPRs) protection. Third, we find that increased competition leads to more financial constraints on firms' innovation activities.

5.1.2. Chapter 3

In Chapter 3, we investigate the extent to which corporate innovation can be affected by government subsidies in China. Using a large panel of 663,699 industrial firms over the period from 1998 to 2008, we find that government subsidies directly boost firms' innovation activities measured by the number of patents filed by firms. The finding verifies the existence of the 'supplement effect' of subsidies to firms' innovation funds in China. As one of the most four important financing sources for firms in China (Allen et al., 2005), subsidies play a directly promoting role in the impressive surge of China's innovation during recent decades.

Next, to alleviate the endogeneity issue between government subsidies and corporation innovation we take more robustness tests. First, since a firm with a large number of patent applications is more likely to obtain subsidies, to ensure the causality between subsidies and innovation we choose the amount of annual public finance revenue divided by the number of firms in each city-year level and the median value of subsidies in each year-city level as the instrumental variables for the subsidy variable. Additionally, we make a quasi-natural experiment by employing a subsample of firms in Suzhou since the revision of subsidy policy for patent applications in one county-level city of Suzhou in 2006 provides an external shock to firms' innovation activities. We make some parallel trend tests and placebo tests to check the validity of the difference-in-differences (DID) setting. The estimation results confirm the causal effect of subsidies on innovation. Second, considering the potential omitted variables in regressions, we add the contemporaneous terms of independent variables into regressions to estimate. Third, taking the potential measurement errors into estimations into account, we use alternative measures of firms' innovation activities by firms' new product output value and R&D expenditure. Last, we take more robustness tests such as using the number of invention patent applications to measure innovation and changing the estimation method to the Zero-inflated Poisson. The results remain qualitatively unchanged.

Further, we extend the direct and positive effect of subsidies to other factors based on firm-level, industry-level, and city-level. First, we check whether the positive effect of subsidies on innovation is varying in different types of ownership structure and financial constraints. We find that the positive effect of subsidies is stronger for private firms and small firms, young firms, firms without political affiliation, firms without state shares, and firms with a high SA index. The finding suggests that subsidies can encourage more innovation activities of these firms as subsidies have a more supplement effect on these firms' innovation funds. Second, we test the positive effect of subsidies based on industry-level. We find that greater industry external finance dependence (EFD) would reduce the positive effect of subsidies while higher industry high tech-intensiveness would enhance the positive effect of subsidies. A higher EFD for firms may reflect a greater borrowing capacity from the financial market, which can eliminate the supplement effect of subsidies on innovation funds. A greater high tech-intensiveness for firms may show more incentives of firms to innovate, so the subsidies obtained could meet the required fund demand of these firms' innovation investments. Third, we explore the positive effect of subsidies in collaboration with city-level factors. We find that higher-level financial development (FD) and higher-level foreign direct investment (FDI) would decrease the positive effect of subsidies. The interpretations of the tightened effects of

FD and FDI are similar. Firms in cities with higher-level FD or higher-level FDI are more likely to get external funds from the banking system or foreign investors, which leads to that the positive effect of subsidies is reduced to some extent.

Last, we investigate the indirect effect of subsidies on corporate innovation. We find that as the proportion of firms with subsidies in one industry-city cluster increases, the positive effect of subsidies on innovation is reduced. As the number of firms obtaining subsidies increases, the amount of subsidies allocated to each firm would be reduced. Thus, the stimulating effect of subsidies on innovation decreases. Additionally, we find that the proportion of firms with subsidies in one industry-city cluster has a significant and positive effect on innovation activities of firms without subsidies instead of firms with subsidies. The finding suggests that subsidies have an spillover effect on the innovation activities of firms without subsidies.

5.1.3. Chapter 4

In chapter 4, we test the extent to which local political turnover affects the finance-innovation nexus in China. Using a large panel of 739,672 industrial firms in 305 cities over the period from 2003 to 2014, we find that city-level financial development can encourage corporation innovation in China. The finding shows that firms can easily obtain external funds with lower costs to innovate from a greater financial development, suggesting that the increasingly higher level of the financial market in China plays an important role in the dramatic surge of China’s innovation over the last decades.

Next, we find political turnover of local government leaders has a positive effect on corporate innovation, which can be explained by the unique political turnover system and government leaders’ promotion ambitions in China. However, political uncertainty arising from local political turnovers negatively affects the positive relationship between city-level financial development and firms' innovation activities. The finding reflects that local political turnover will make higher costs of external finance although political turnover itself can promote corporate innovation. In the Chinese context where political influence in the social and economic life is pervasive, political turnover greatly affects firms' decisions of innovation investments including the external financing sources of R&D.

We take more tests to check robustness. First, we use an IV Tobit estimation to solve the issue of reverse causality. We choose the fraction of senior citizens as the instrumental variable for financial development since seniors are more likely to consume less but deposit more compared to young people. We choose the predicted political turnovers as the instrumental variable for political turnovers. The estimation results confirm the causality between financial development and innovation and the causality between political turnover and innovation. Second, we choose alternative measures of financial development, political turnover, and innovation to estimate again, considering potential measurement errors of the regression variables. Third, we augment our regression models by covering the contemporaneous terms of regression variables to avoid the issue of potential omitted variables. Fourth, we make more robustness tests by dropping firms with sales of less than 20 million CNY, dropping firms in four municipalities and county-level cities, changing estimation methods to the Zero-inflated Poisson or the Pooled Probit. All estimation results keep qualitatively consistent.

Furthermore, we make extensions to other factors. First, we find that the negative effect of political uncertainty arising from local political turnovers on the positive relationship between financial development and corporation innovation is stronger for firms facing abnormal political turnovers than firms with normal political turnovers. Second, we find that compared to firms without political connections, the negative effect of local political turnover is more pronounced for firms with political connections since local political turnover would hurt more to these firms' external financing sources from the banking system mainly controlled by state capitals. Third, we find the negative effect of local political turnover is more pronounced for firms with less financial constraints instead of firms with more financial constraints, as local political turnover would harm more to external financing sources of firms less financial constraints which rely more on external finance.

5.2. Policy implications

First of all, the findings in the thesis suggest that industry competition, government subsidies, and political turnover play critical roles in China's corporate innovation. First, due to the negative effect of severe industry competition in China, governments need to deepen structural reforms to eliminate over-competition. Chinese governments also need to continue to upgrade low-end manufacturing to high-tech industries to develop the quality of goods 'made in China'. For example, governments should use policies to strengthen IPRs and tax relief, which benefits to stimulate corporate innovation and upgrade industry structure. Since EFD can amplify the negative effect of competition on innovation and firms with higher financial constraints suffer more, governments need to deepen the financial system reform and further open the financial market in China, which can alleviate the issues of the 'lending bias' and the 'institutional discrimination' to financially constrained firms. Additionally, governments need to issue more policies to help firms to avoid overwhelming dependence on external finance and lower leverage ratios, which also can promote corporate innovation.

Second, since subsidies could promote firms' innovation activities by supplementing innovation funds, governments should use more subsidy policies to encourage firms' innovation incentives. Additionally, considering that the positive effect of subsidies on corporate innovation is various, governments should further adjust the objective mechanism of subsidy policies. More subsidies should be allocated to private firms and financially constrained firms as the positive effect of subsidies on innovation activities is stronger for these firms. Furthermore, for the industry-level, more subsidies should be allocated to firms in industries with lower EFD since these firms usually do not get a strong ability to get external funds to innovate; more subsidies should be distributed to firms in industries with greater high tech-intensiveness to meet the fund demand of these firms' large innovation investments. For the city-level, more subsidies should be given to firms located in cities with lower levels of financial development and foreign direct investment as more types of external financing sources will alleviate the positive effect of subsidies on innovation. Governments also need to increase the proportion of firms obtaining subsidies rather than allocate a large amount of subsidies to some specific firms, which also can motivate firms without subsidies to innovate.

Third, because financial development has a significant and positive effect on corporate innovation, governments in China should deepen the financial system reform to efficiently allocate financial sources to firms, which can encourage firms' innovation investments then boost economic development. Second, due to the promoting effect of local political turnover on innovation, governments should establish and improve a political turnover system based on local development needs, which can stimulate corporate innovation through necessary political turnovers. Additionally, since political uncertainty caused by local political turnover reduces the positive effect of financial development on corporate innovation, governments also need to implement some policy tools to ensure financial market stability when the local political environment changes. Meanwhile, as the negative effect of local political turnover on the positive effect of financial development on innovation is more pronounced for firms with abnormal political turnovers, firms with political connections, and firms with lower financial constraints, when these firms face political turnovers governments should use some policy schemes such as subsidies to ensure their external financing capitals stable. Governments also need to encourage firms to reduce their overwhelming dependence on external finance.

5.3. Suggestions for future research

In chapter 2, we focus on a large panel of industrial firms in China over the period from 1998 to 2007. However, after the 2008 financial crisis and the economic development in the past ten years, China's economy also changed a lot. If we have opportunities, further research should try to extend the data period based on unlisted and listed firms to observe whether the negative effect of competition on innovation could hold for a long period in China.

In chapter 3, we first find a direct and positive effect of subsidies on corporate innovation in China. Subsequently, we successfully test a spillover effect of subsidies on innovation activities of firms without subsidies. We could make further research to investigate the spillover effect of subsidies in more detail and observe what is the difference between the direct effect and the spillover effect of subsidies in some classifications.

In chapter 4, we find that local political turnover reduces the positive effect of financial development on corporate innovation, and further explore the negative effect of political turnover based on some other aspects. Future research could explore the negative effect of political turnover to link with more aspects of political turnovers, e.g. the places where appointed leaders come, the ways of political turnovers for outgoing leaders (promotion, equal position transfer, resign voluntarily, retirement or prison), or for appointed leaders (promotion or equal position transfer). We also can search for some exogenous policy shocks to financial development or political turnover, to set up a DID test, which may better confirm the causality between financial development and innovation, or political turnover and innovation.

Chapter 5
Conclusions

The thesis focuses all “above-scale” enterprises including unlisted firms and listed firms. However, there is a big difference in firms’ investment decisions, financing ability, governance structure, and management level between listed firms and unlisted firms. Some studies show that compared to unlisted firms listed firms may not face higher financial constraints due to their strong financing capacity from the equity market (Allen et al., 2005), thus the negative effect of increased competition is possibly weaker for listed firms. Additionally, because listed firms have to face supervision from equity investors, own a relatively higher governance level compared to unlisted firms, listed firms may have a potential strong ability to eliminate the negative effect of competition, efficiently use subsidies or the funds from the banking system to innovation, and avoid the negative effect of political turnover caused by local political turnover on their external financing sources. In the future we can try to find some identifiers to distinguish listed firms and unlisted firms in the NBS firm-level dataset. It is worth exploring the difference between unlisted firms and listed firms in the effect of competition, subsidies, and political turnover on innovation, which can provide new insight into the understanding of the marvellous economic development in China over the few decades.

References

Aboody, D. and Lev, B., 2000. Information asymmetry, R&D, and insider gains. *Journal of Finance*, *55*(6): 2747-2766.

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N. and Kerr, W., 2018. Innovation, reallocation, and growth. *American Economic Review*, *108*(11): 3450-91.

Acharya, V. and Xu, Z., 2017. Financial dependence and innovation: The case of public versus private firms. *Journal of Financial Economics*, *124*(2): 223-243.

Acharya, V.V. and Subramanian, K.V., 2009. Bankruptcy codes and innovation. *Review of Financial Studies*, *22*(12)： 4949-4988.

Aerts, K. and Schmidt, T., 2008. Two for the price of one?: Additionality effects of R&D subsidies: A comparison between Flanders and Germany. *Research Policy*, *37*(5): 806-822.

Aghion, P. and Howitt, P., 1992. A model of growth through creative destruction. *Econometrica*, 60(3): 488-500.

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P., 2005. Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, *120*(2): 701-728.

Aghion, P., Cai, J., Dewatripont, M., Du, L., Harrison, A. and Legros, P., 2015. Industrial policy and competition. *American Economic Journal: Macroeconomics*, *7*(4): 1-32.

Aghion, P., Van Reenen, J. and Zingales, L., 2013. Innovation and institutional ownership. *American Economic Review*, *103*(1): 277-304.

Allen, F. and Gu, X., 2015. China's financial system: growth and risk. *Foundations and Trends® in Finance*, *9*(3–4): 197-319.

Allen, F., Qian, J. and Qian, M., 2005. Law, finance, and economic growth in China. *Journal of Financial Economics*, 77(1): 57-116.

Allen, F., Qian, J.Q. and Qian, M., 2019. A review of China's institutions. *Annual Review of Financial Economics*, *11*: 39-64.

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.

Amore, M.D. and Minichilli, A., 2018. Local political uncertainty, family control, and investment behavior. *Journal of Financial and Quantitative Analysis*, *53*(4): 1781-1804.

An, H., Chen, Y., Luo, D. and Zhang, T., 2016. Political uncertainty and corporate investment: Evidence from China. *Journal of Corporate Finance*, *36*: 174-189.

Ang, J.B. and Kumar, S., 2014. Financial development and barriers to the cross-border diffusion of financial innovation. *Journal of Banking and Finance*, *39*: 43-56.

Anton, J.J. and Yao, D.A., 2002. The sale of ideas: Strategic disclosure, property rights, and contracting. *Review of Economic Studies*, *69*(3): 513-531.

Arrow, K.J., 1972. Economic welfare and the allocation of resources for invention. In *Readings in industrial economics* (pp. 219-236). Palgrave, London.

Ayyagari, M., Demirgüç-Kunt, A. and Maksimovic, V., 2010. Formal versus informal finance: Evidence from China. *Review of Financial Studies*, 23(8): 3048-3097.

Ayyagari, M., Demirgüç-Kunt, A. and Maksimovic, V., 2011. Firm innovation in emerging markets: The role of finance, governance, and competition. *Journal of Financial and Quantitative Analysis, 46*(6): 1545-1580.

Bagwell, K. and Staiger, R.W., 1989. The role of export subsidies when product quality is unknown. *Journal of International Economics*, *27*(1-2): 69-89.

Bagwell, K. and Staiger, R.W., 2006. Will international rules on subsidies disrupt the world trading system?. *American Economic Review*, 96(3): 877-895.

Becker, B., 2007. Geographical segmentation of US capital markets. *Journal of Financial Economics*, 85: 151-178.

Bernanke, B. and Gertler, M., 1989. Agency costs, net worth, and business fluctuations. *American Economic Review*, 14-31.

Bhattacharya, U., Hsu, P.H., Tian, X. and Xu, Y., 2017. What affects innovation more: policy or policy uncertainty?. *Journal of Financial and Quantitative Analysis*, *52*(5): 1869-1901.

Bloom, N., 2007. Uncertainty and the Dynamics of R&D. *American Economic Review*, *97*(2): 250-255.

Blundell, R., Griffith, R. and Van Reenen, J., 1999. Market share, market value and innovation in a panel of British manufacturing firms. *Review of Economic Studies*, 66(3): 529-554.

Boeing, P., 2016. The allocation and effectiveness of China's R&D subsidies – Evidence from listed firms. *Research Policy*, 45(9): 1774-1789.

Boeing, P., Mueller, E. and Sandner, P., 2016. China's R&D explosion – Analyzing productivity effects across ownership types and over time. *Research Policy*, 45(1): 159-176.

Bond, S. and Meghir, C., 1994. Dynamic investment models and the firm's financial policy. *Review of Economic Studies*, 61(2):197-222.

Bond, S. and Van Reenen, J., 2007. Microeconometric models of investment and employment. *Handbook of Econometrics*, *6*: 4417-4498.

Bond, S., Elston, J.A., Mairesse, J. and Mulkay, B., 2003. Financial factors and investment in Belgium, France, Germany, and the United Kingdom: A comparison using company panel data. *Review of Economics and Statistics*, *85*(1): 153-165.

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.

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

Brown, J.R., Fazzari, S.M. and Petersen, B.C., 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance*, 64(1): 151-185.

Brown, J.R., Martinsson, G. and Petersen, B.C., 2012. Do financing constraints matter for R&D?. *European Economic Review*, 56(8): 1512-1529.

Bushee, B.J., 1998. The influence of institutional investors on myopic R&D investment behavior. *Accounting Review*, 305-333.

Busom, I., 2000. An Empirical Evaluation of the Effects of R\&D Subsidies. *Economics of Innovation and New Technology*, *9*(2): 111-148.

Butler, A.W. and Cornaggia, J., 2011. Does access to external finance improve productivity? Evidence from a natural experiment. *Journal of Financial Economics*, *99*(1): 184-203.

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

Campbell, D.E. and Kelly, J.S., 1994. Trade-off theory. *American Economic Review*, 84(2): 422-426.

Campbell, J.Y., Lettau, M., Malkiel, B.G. and Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, *56*(1): 1-43.

Carman, J.M. and Dominguez, L.V., 2001. Organizational transformations in transition economies: Hypotheses. *Journal of Macromarketing*, 21(2): 164-180.

Carpenter, R.E., Fazzari, S.M., Petersen, B.C., Kashyap, A.K. and Friedman, B.M., 1994. Inventory investment, internal-finance fluctuations, and the business cycle. *Brookings Papers on Economic Activity*, 1994(2): 75-138.

Chang, S.J. and Wu, B., 2014. Institutional barriers and industry dynamics. *Strategic Management Journal*, *35*(8): 1103-1123.

Chen, L. and Naughton, B., 2016. An institutionalized policy-making mechanism: China's return to techno-industrial policy. *Research Policy*, 45(10): 2138-2152.

Chen, S., Mao, H. and Feng, Z., 2020. Political uncertainty and firm entry: Evidence from Chinese manufacturing industries. *Journal of Business Research*, *120*: 16-30.

Chen, V.Z., Li, J., Shapiro, D.M. and Zhang, X., 2014. Ownership structure and innovation: An emerging market perspective. *Asia Pacific Journal of Management*, 31(1): 1-24.

Chirinko, R.S. and Schaller, H., 1995. Why does liquidity matter in investment equations?. *Journal of Money, Credit and Banking*, 27(2): 527-548.

Chow, C.K., Song, F.M. and Wong, K.P., 2010. Investment and the soft budget constraint in China. *International Review of Economics and Finance*, 19(2): 219-227.

Clarysse, B., Wright, M. and Mustar, P., 2009. Behavioural additionality of R&D subsidies: A learning perspective. *Research Policy*, *38*(10): 1517-1533.

Coad, A., Segarra, A. and Teruel, M., 2016. Innovation and firm growth: Does firm age play a role? *Research Policy*, 45(2): 387-400.

Cong, R., 2001. Marginal effects of the tobit model. *Stata Technical Bulletin*, 10(56).

Cornaggia, J., Y. Mao, X. Tian, and B. Wolfe., 2015. Does banking competition affect innovation? *Journal of Financial Economics*, 115(1): 189-209.

Criscuolo, C., Haskel, J.E. and Slaughter, M.J., 2010. Global engagement and the innovation activities of firms. *International Journal of Industrial Organization*, 28(2): 191-202.

Cuervo, A. and Villalonga, B., 2000. Explaining the variance in the performance effects of privatization. *Academy of Management Review*, 25(3): 581-590.

Czarnitzki, D. and Hottenrott, H., 2011. R&D investment and financing constraints of small and medium-sized firms. *Small Business Economics*, 36(1): 65-83.

Dang, J. and Motohashi, K., 2015. Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. *China Economic Review, 35*: 137-155.

David, P.A., Hall, B.H. and Toole, A.A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy*, 29(4-5): 497-529.

Dechow, P.M., Kothari, S.P. and Watts, R.L., 1998. The relation between earnings and cash flows. *Journal of Accounting and Economics*, 25(2): 133-168.

Ding, S., Guariglia, A. and Knight, J., 2013. Investment and financing constraints in China: does working capital management make a difference?. *Journal of Banking and Finance*, 37(5): 1490-1507.

Dixit, A.K. and Stiglitz, J.E., 1977. Monopolistic competition and optimum product diversity. *American Economic Review*, *67*(3): 297-308.

Djankov, S., La Porta, R., Lopez-de-Silanes, F. and Shleifer, A., 2002. The regulation of entry. *Quarterly Journal of Economics*, *117*(1): 1-37.

EY (2018). How does geopolitical dynamics affect future China overseas investment? *China Go Abroad* (8th issue). China Mergers & Acquisitions Association.

Fan, G., Wang, X., Zhu, H., 2016. *NERI index of marketisation for China's provinces: 2016 report (in Chinese)*. Beijing: Economic Science Press.

Fang, J. and Walsh, M., 2018. Made in China 2025: Beijing's manufacturing blueprint and why the world is concerned. Available at: https://www.abc.net.au/news/2018-04-29/why-is-made-in-china-2025-making-people-angry/9702374.

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

Fang, L.H., Lerner, J., Wu, C. and Zhang, Q., 2018. Corruption, Government Subsidies, and Innovation: Evidence from China. *Harvard Business School Entrepreneurial Management Working Paper*, 19-031.

Fazzari, S.M., Hubbard, R.G., Petersen, B.C., Blinder, A.S. and Poterba, J.M., 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity*, 1988(1): 141-206.

Feldman, M.P. and Kelley, M.R., 2006. The ex ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research Policy*, *35*(10): 1509-1521.

Fisman, R. and Love, I., 2003. Trade credit, financial intermediary development, and industry growth. *Journal of Finance*, *58*(1): 353-374.

Fisman, R. and Love, I., 2004. Financial development and intersectoral allocation: A new approach. *Journal of Finance*, *59*(6): 2785-2807.

Francis, B.B., Hasan, I. and Zhu, Y., 2014. Political uncertainty and bank loan contracting. *Journal of Empirical Finance*, *29*: 281-286.

Ge, Y. and Qiu, J., 2007. Financial development, bank discrimination and trade credit. *Journal of Banking and Finance*, *31*(2): 513-530.

Giroud, X. and Mueller, H.M., 2010. Does corporate governance matter in competitive industries? *Journal of Financial Economics*, 95(3): 312-331.

Godement, F., Parello-Plesner, J. and Richard, A., 2011. The Scramble for Europe. European Council on Foreign Relations. Available at: https://www.ecfr.eu/page/-/ECFR37_Scramble_For_Europe_AW_v4.pdf.

González, X. and Pazó, C., 2008. Do public subsidies stimulate private R&D spending?. *Research Policy*, *37*(3): 371-389.

Görg, H. and Strobl, E., 2007. The effect of R&D subsidies on private R&D. *Economica*, *74*(294): 215-234.

Greenwood, J. and Jovanovic, B., 1990. Financial development, growth, and the distribution of income. *Journal of Political Economy*, *98*(5, Part 1): 1076-1107.

Greve, H.R., 2003. A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, 46(6): 685-702.

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4): 1661-1707.

Griliches, Z., Pakes, A., Hall, B., 1986. *The value of patents as indicators of inventive activity*. NBER working paper no. 2083.

Guariglia, A. and Liu, P., 2014. To what extent do financing constraints affect Chinese firms' innovation activities? *International Review of Financial Analysis*, 36: 223-240.

Guariglia, A. and Mateut, S., 2016. External finance and trade credit extension in China: does political affiliation make a difference?. *European Journal of Finance*, 22(4-6): 319-344.

Guariglia, A. and Yang, J., 2016. A balancing act: Managing financial constraints and agency costs to minimize investment inefficiency in the Chinese market. *Journal of Corporate Finance*, 36: 111-130.

Guariglia, A., Liu, X. and Song, L., 2011. Internal finance and growth: Microeconometric evidence on Chinese firms. *Journal of Development Economics*, *96*(1): 79-94.

Guo, D., Guo, Y. and Jiang, K., 2016. Government-subsidized R&D and firm innovation: Evidence from China. *Research Policy*, *45*(6): 1129-1144.

Hadlock, C.J. and Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, *23*(5) 1909-1940.

Hagedoorn, J. and Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators?. *Research Policy*, *32*(8): 1365-1379.

Harhoff, D., 2000. Are there financing constraints for R&D and investment in German manufacturing firms?. *The economics and econometrics of innovation.* Springer, US, 399-434.

Hashmi, A.R., 2013. Competition and innovation: The Inverted-U relationship revisited. *Review of Economics and Statistics*, 95(5): 1653-1668.

Haushalter, D., S. Klasa, and W. Maxwell., 2007. The influence of product market dynamics on a firm's cash holdings and hedging behavior. *Journal of Financial Economics*, 84(3): 797-825.

He, Q., Xue, C. and Zhu, C., 2017. Financial development and patterns of industrial specialization: Evidence from China. *Review of Finance*, *21*(4): 1593-1638.

He, Z.L., Tong, T.W., Zhang, Y. and He, W., 2018. A database linking Chinese patents to China’s census firms. *Scientific data*, *5*(1): 1-16.

Henard, D.H. and Szymanski, D.M., 2001. Why some new products are more successful than others. *Journal of Marketing Research*, 38(3): 362-375.

Hoberg, G., Phillips, G. and Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. *Journal of Finance*, *69*(1): 293-324.

Holmstrom, B., 1989. Agency costs and innovation. *Journal of Economic Behavior and Organization*, *12*(3): 305-327.

Holz, C.A., 2009. No razor’s edge: Reexamining Alwyn Young's evidence for increasing interprovincial trade barriers in China. Review of Economics and Statistics, 91(3): 599-616.

Hormats, R.D., 2011. Addressing the Challenges of the China Model. https://china.usc.edu/robert-hormats-addressing-challenges-china-model-may-11-2011.

Hsieh, C.T. and Klenow, P.J., 2009. Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, *124*(4): 1403-1448.

Hsu, P.H., Tian, X. and Xu, Y., 2014. Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112(1): 116-135.

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.

Huang, Y., 2003. *Selling China: Foreign direct investment during the reform era*. Cambridge University Press.

Jiang, F. and Kim, K.A., 2020. Corporate governance in China: A survey. *Review of Finance*, *24*(4): 733-772.

Johnson, S. and Mitton, T., 2003. Cronyism and capital controls: evidence from Malaysia. *Journal of Financial Economics*, 67(2): 351-382.

Khwaja, A.I. and Mian, A., 2005. Do lenders favor politically connected firms? Rent provision in an emerging financial market. *Quarterly Journal of Economics*, 120(4): 1371-1411.

Kleer, R., 2010. Government R&D subsidies as a signal for private investors. *Research Policy*, 39(10): 1361-1374.

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, *132*(2): 665-712.

Kou, Z. and Liu, X., 2017. *FIND report on city and industrial innovation in China (2017)*. Fudan Institute of Industrial Development, School of Economics, Fudan University.

Lee, E., Walker, M. and Zeng, C., 2014. Do Chinese government subsidies affect firm value?. *Accounting, Organizations and Society*, 39(3): 149-169.

Lee, E., Walker, M. and Zeng, C.C., 2017. Do Chinese state subsidies affect voluntary corporate social responsibility disclosure?. *Journal of Accounting and Public Policy*, *36*(3): 179-200.

Lei, Z., Sun, Z. and Wright, B., 2012. Patent subsidy and patent filing in China. *University of California, Berkeley, mimeo*.

Lerner, J., 1999. The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program. *The Journal of Business*, *72*(3): 285-318.

Levin, R.C., Cohen, W.M. and Mowery, D.C., 1985. R & D appropriability, opportunity, and market structure: new evidence on some Schumpeterian hypotheses. *American Economic Review*, 75(2): 20-24.

Levine, R., 1991. Stock markets, growth, and tax policy. *Journal of Finance*, *46*(4): 1445-1465.

Levine, R., Loayza, N. and Beck, T., 2000. Financial intermediation and growth: Causality and causes. *Journal of Monetary Economics*, *46*(1): 31-77.

Li, H., Meng, L., Wang, Q. and Zhou, L.A., 2008. Political connections, financing and firm performance: Evidence from Chinese private firms. *Journal of Development Economics*, 87(2): 283-299.

Li, X., 2012. Behind the recent surge of Chinese patenting: An institutional view. *Research Policy*, *41*(1): 236-249.

Liang, Q. and Jian-Zhou, T., 2006. Financial development and economic growth: Evidence from China. *China Economic Review*, *17*(4): 395-411.

Liang, X., Lu, X. and Wang, L., 2012. Outward internationalization of private enterprises in China: The effect of competitive advantages and disadvantages compared to home market rivals. *Journal of World Business*, 47(1): 134-144.

Lim, C.Y., Wang, J. and Zeng, C.C., 2018. China's “mercantilist” government subsidies, the cost of debt and firm performance. *Journal of Banking and Finance*, *86*: 37-52.

Lin, J.Y. and Tan, G., 1999. Policy burdens, accountability, and the soft budget constraint. *American Economic Review*, *89*(2): 426-431.

Lin, S. and Ye, H., 2017. Foreign direct investment, trade credit, and transmission of global liquidity shocks: Evidence from Chinese manufacturing firms. *Review of Financial Studies*, *31*(1): 206-238.

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.

Love, I., 2003. Financial development and financing constraints: International evidence from the structural investment model. *Review of Financial Studies*, *16*(3): 765-791.

Lundstrum, L.L., 2002. Corporate investment myopia: a horserace of the theories. *Journal of Corporate Finance*, *8*(4): 353-371.

Lyandres, E. and Palazzo, B., 2016. Cash holdings, competition, and innovation. *Journal of Financial and Quantitative Analysis*, 51(6), 1823-1861.

Maskin, E., Qian, Y. and Xu, C., 2000. Incentives, information, and organizational form. *Review of Economic Studies*, *67*(2): 359-378.

Mei, J. and Guo, L., 2004. Political uncertainty, financial crisis and market volatility. *European Financial Management*, *10*(4): 639-657.

Myers, N., 2001. *Perverse subsidies: how tax dollars can undercut the environment and the economy*. Island Press.

Myers, S.C., 1984. The Capital Structure Puzzle. *Journal of Finance*, *39*(3): 574-592.

Myers, S.C. and Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2): 187-221.

Nagar, V., Schoenfeld, J. and Wellman, L., 2019. The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, *67*(1): 36-57.

Nelson, R.R., 1959. The simple economics of basic scientific research. *Journal of Political Economy*, 67(3): 297-306.

Newey, W.K., 1987. Efficient estimation of limited dependent variable models with endogenous explanatory variables. *Journal of Econometrics*, *36*(3): 231-250.

Nickell, S.J., 1996. Competition and corporate performance. *Journal of Political Economy*, 104(4): 724-746.

OECD, 2017. Research and Development Statistics (RDS). Available at: http://www.oecd.org/science/inno/researchanddevelopmentstatisticsrds.htm.

OECD, 2018. Gross domestic spending on R&D (indicator). Available at: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm.

Ovtchinnikov, A.V., Reza, S.W. and Wu, Y., 2020. Political activism and firm innovation. *Journal of Financial and Quantitative Analysis*, *55*(3): 989-1024.

Peress, J., 2010. Product market competition, insider trading, and stock market efficiency. *Journal of Finance*, 65(1): 1-43.

Pertuze, J.A., Reyes, T., Vassolo, R.S. and Olivares, N., 2019. Political uncertainty and innovation: The relative effects of national leaders' education levels and regime systems on firm-level patent applications. *Research Policy*, *48*(9): 103808.

Piotroski, J.D. and Zhang, T., 2014. Politicians and the IPO decision: The impact of impending political promotions on IPO activity in China. *Journal of Financial Economics, 111*(1): 111-136.

Rajan, R.G. and Zingales, L., 1998. Financial dependence and growth. *American Economic Review, 88*(3): 559-586.

Romer, P.M., 1990. Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2): S71-S102.

Rong, Z., Wu, X. and Boeing, P., 2017. The effect of institutional ownership on firm innovation: Evidence from Chinese listed firms. *Research Policy*, 46(9): 1533-1551.

Ru, H., 2018. Government credit, a double-edged sword: Evidence from the China Development Bank. *Journal of Finance*, *73*(1): 275-316.

Saint-Paul, G., 1992. Technological choice, financial markets and economic development. *European Economic Review*, *36*(4): 763-781.

Scherer, F.M., 1967. Market Structure and the Employment of Scientists and Engineers. *The American Economic Review*. 57(3): 524-531.

Schumpeter, J.A., 1911. *The Theory of Economics Development*. Harvard University Press, Cambridge, MA.

Schumpeter, J.A., 1943. *Capitalism, Socialism and Democracy*. London, Allen Unwin.

Schwartz, G. and Clements, B., 1999. Government subsidies. *Journal of Economic Surveys*, *13*(2): 119-148.

Shen, C.H.H. and Zhang, H., 2018. Tournament incentives and firm innovation. *Review of Finance*, *22*(4): 1515-1548.

Smith, R.J. and Blundell, R.W., 1986. An exogeneity test for a simultaneous equation Tobit model with an application to labor supply. *Econometrica: Journal of the Econometric Society*, 679-685.

Solow, R.M., 1957. Technical change and the aggregate production function. *Review of Economics and Statistics*, *39*(3): 312-320.

Song, Z., Storesletten, K. and Zilibotti, F., 2011. Growing like China. *American Economic Review*, *101*(1): 196-233.

Staiger, D. and Stock, J.H., 1997. Instrumental Variables Regression with Weak Instruments. *Econometrica*, 65(3): 557-586.

Stein, J.C., 1988. Takeover threats and managerial myopia. *Journal of Political Economy*, *96*(1): 61-80.

Stiglitz, J.E., 1989. Markets, market failures, and development. *American Economic Review,* 79(2): 197-203.

Stock, J.H. and Yogo, M., 2005. 'Testing for weak instruments in linear IV regression,' in (Andrews, D.W. and Stock, J.H. eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg,* 80-108. Cambridge University Press, Cambridge, MA.

Tether, B. S., 2002. Who co-operates for innovation, and why: an empirical analysis. *Research Policy*, *31*(6): 947-967.

Tingvall, P.G. and Poldahl, A., 2006. Is there really an inverted U-shaped relation between competition and R&D?. *Economics of Innovation and New Technology*, 15(2): 101-118.

Tobin, J., 1958. *Estimation of relationships for limited dependent variables*. *Econometrica: Journal of the Econometric Society*, 24-36.

Vavra, J., 2014. Inflation dynamics and time-varying volatility: New evidence and an ss interpretation. *Quarterly Journal of Economics*, *129*(1): 215-258.

Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica: *Journal of the Econometric Society*, 307-333.

Wallsten, S.J., 2000. The effects of government-industry R&D programs on private R&D: the case of the Small Business Innovation Research program. *RAND Journal of Economics*, *31*(1): 82-100.

Wang, J. and Wang, X., 2015. Benefits of foreign ownership: Evidence from foreign direct investment in China. *Journal of International Economics*, *97*(2): 325-338.

Whited, T.M., 1992. Debt, liquidity constraints, and corporate investment: Evidence from panel data. *Journal of Finance*, 47(4): 1425-1460.

World Bank, 2006. China - Governance, investment climate, and harmonious society: Competitiveness enhancement for 120 cities in China. Washington, DC: World Bank.

Wu, J., 2012. Technological collaboration in product innovation: The role of market competition and sectoral technological intensity. *Research Policy*, 41(2): 489-496.

Xiao, S. and Zhao, S., 2012. Financial development, government ownership of banks and firm innovation. *Journal of International Money and Finance*, *31*(4): 880-906.

Xu, N., Chen, Q., Xu, Y. and Chan, K.C., 2016. Political uncertainty and cash holdings: Evidence from China. *Journal of Corporate Finance, 40*: 276-295.

Xu, N., Xu, X. and Yuan, Q., 2013. Political connections, financing friction, and corporate investment: Evidence from Chinese listed family firms. *European Financial Management*, 19(4): 675-702.

Young, A., 2000. The razor's edge: Distortions and incremental reform in the People's Republic of China. Quarterly Journal of Economics, 115(4): 1091-1135.

Yu, F., Guo, Y., Le-Nguyen, K., Barnes, S.J. and Zhang, W., 2016. The impact of government subsidies and enterprises' R&D investment: A panel data study from renewable energy in China. *Energy Policy*, 89: 106-113.

Zhang, C., Zhu, Y. and Lu, Z., 2015. Trade openness, financial openness, and financial development in China. *Journal of International Money and Finance*, *59*: 287-309.

Zhang, J., Wang, L. and Wang, S., 2012. Financial development and economic growth: Recent evidence from China. *Journal of Comparative Economics*, *40*(3): 393-412.

Zhu, X., Asimakopoulos, S. and Kim, J., 2020. Financial development and innovation-led growth: Is too much finance better?. *Journal of International Money and Finance*, *100*: 102083.