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Inside China's "Growth Miracle:" A Structural Framework of Firm Concentration, Innovation and Performance with Policy Distortions

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by

Anthony J. Howell

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Abstract of the Dissertation

Inside China's "Growth Miracle:" A Structural Framework of Firm Concentration, Innovation and Performance with Policy Distortions

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Anthony J. Howell

Doctor of Philosophy in Geography

University of California, Los Angeles, 2014

Professor Cindy Fan, Chair

Since the first economic reforms were enacted in 1978, China experienced double digit growth for over three decades leading it to become the second largest economy by 2010. What accounts for China's unparalleled economic growth in a relatively short time period? To provide new insights into the unique dimensions of China's spectacular growth "miracle", this dissertation relies on a set of micro-economic analyses into the changing firm, industrial and regional dynamics underway in China. Drawing from theories emanating from the innovation, economic geography and public policy literatures, a key aspect of this research empirically estimates the direct and cross-scalar interaction effects of firm-level characteristics, industrial agglomeration and the policy environment on firm performance. Using detailed firm-level data, the heterogeneous short- and long-run impacts of policy-induced economic distortions are respectively evaluated within three separate relationships to firm performance: (1) innovation; (2) agglomeration; and (3) a geo-economic innovation framework. The results produced in this dissertation highlight the importance of institution building, coinciding along with the need to reduce the role of state intervention in the market. Building a solid institutional environment reduces the high risks associated with pursuing innovation and will help facilitate the transfer of tacit knowledge leading to positive externalities, thereby reducing firm dependency on state protectionism, and spurring firm competitiveness.

The dissertation of Anthony J. Howell is approved.

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2014

To my loving parents who have supported me every step of the way and without whom I would not be here today. I want to thank you both from the bottom of my heart for making so many sacrifices, during both the hard times and the good times, to raise me to be the man I am today and for saving me from taking the wrong path in life. I owe my success to you both and hope that I have the chance to return all of your love and support. To my committee members, thank you all for your support and guidance over the years, and to David for helping me to carefully revise and polish this dissertation work. To my amazing advisor, Cindy Fan, who for the past five years has always been in my corner mentoring me and encouraging me to pursue my goals and ambitions. Perhaps, most importantly was the day you invited me to meet Canfei in February 2012 and the three of us established a research collaboration that has already resulted in many positive and unexpected outcomes. From that day on the nature of my research evolved tremendously. Following Canfei's invitation to Peking University, I spent my Fulbright year working with him in the Geography Department, where I was able to challenge myself and apply my statistical skill-set in new and fascinating ways to study pressing issues facing China. I also enjoyed the great privilege of being warmly welcomed to partake in the departmental activities, and had the chance to establish many new friendships throughout the year. Beyond professional development, my Fulbright experience also deeply impacted me personally as I met the beautiful girl of my dreams. I dedicate this dissertation research to my love Kiran Choudhry. I love you and am excited to be with you in China and to share our future together.

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CHAPTER 1

Introduction

1.1 Background

China is the world's largest transitioning country with a strong socialist legacy that has achieved an unprecedented development "miracle" in modern times, averaging double digit growth over the past 30 years. Since economic reforms were implemented in 1978, and following its subsequent economic growth, China has emerged as a key actor in the global economy. In 2000, China's share of global manufacturing output was only 5.7% (Nahm and Steinfeld, 2012). This represented only one-quarter that of the U.S. economic output. By 2011, China surpassed the U.S. to become the top global manufacturing producer, increasing its share to 19.8% of global output.

What accounts for China's unparalleled economic growth in such a short time period? The conventional view is that China has capitalized on several advantages such as cheap, abundant labor supply, state subsidies and a growing local demand for consumer items. While this perspective may explain, in part, China's manufacturing success, it does not account for why other countries with low factor prices, state-incentives and even large domestic markets have not achieved the same level of success as China.

The theoretical frameworks and empirical methodologies adopted in this dissertation attempt to more accurately account for China's unique growth story. This dissertation is informed by, integrates and contributes to several bodies of literature – innovation, economic geography and public policy. Emanating from the literatures, I identify and examine three main determinants of firm performance: industrial agglomeration, innovation and public policy. Industrial agglomeration induces innovation, most notably via knowledge spillovers, while public policy can introduce distortions into the economy that can greatly affect both agglomeration and innovation. Agglomeration, innovation and policy are therefore, examined in relation to one another for the purposes of studying their independent and combined effects on firm performance.

1.2 Agglomeration and Innovation: The 'Missing' Explanatory Factors Behind Chinese Growth

A striking feature of China's new spatial economy is the fusion of centripetal market forces and state policy acting heterogeneously on industrial activity, where state-selected industries, cities and regions have witnessed intense industrialization and industrial agglomeration – the concentration of economic activity in officially designated special and open economic zones. Large manufacturing belts and state-orchestrated industrial clusters, especially in the Pearl River Delta, Yangze River Delta and Beijing-Tianjin Corridor, are now a prominent aspect of the Chinese spatial landscape.

The designation of special economic zones (SEZs) and development of industrial clusters that emerged following economic reforms are recognized as being two important engines of China's extraordinary growth (Zeng, 2010). This is due, in part, to the increasing degree of vertical integration of the production process. In other words, the co-location of a large number of specialized firms has resulted in the production process becoming increasingly disaggregated into small incremental stages, leading to efficiency gains for firms located within agglomerated regions (Fan and Scott, 2003; Long and Zhang, 2011).

Considerable research has been carried out on the evolution of China's industrial agglomerations, albeit very few studies have tracked firm performance over a long period of time – often due to accessibility issues (Sonobe and Otsuka, 2006). Even fewer studies compare the actual responses of Chinese firms located inside and outside agglomerated regions to protectionist government policies (Barbieria et al., 2010). Moreover, the empirical literature that does examine the effects of agglomeration on Chinese firm performance generally do not take into account the recent developments made in the 'new 'new' economic geography' (NNEG)(Ottaviano, 2011; Baldwin and Okubo, 2006; Venables, 2011; Behrens and Duranton, 2010; Combes et al., 2012). The NNEG literature introduces heterogeneous firm models to offer new insights into the effects of agglomeration on firm productivity. Based on this line of research, the new agglomeration literature identifies spatial sorting (high-productivity firms seek out concentrated areas) and firm selection (low-productivity firms are forced out of high concentrated areas due to competitive pressures) as two additional explanations to urban increasing returns that may explain the empirically observed urban premium – firms produce more in agglomerative regions than firms located elsewhere.

In addition to industrial clustering, Nahm and Steinfeld (2012) offer new insight to explain why other developing countries with large domestic markets and cheap factor inputs have not experienced the same degree of success as China. The authors argue that "innovative manufacturing" is a critical part of, and the "missing" explanatory factor that accounts for China's unique economic growth story. This perspective is in stark contrast to the conventional view that the manufacturing - physical assembling - process takes place in strict isolation from the innovation process (Steinfeld, 2004a). Moreover, recognizing the important role of innovation in Chinese manufacturing challenges the stereotypical perceptions of China as being merely "the world's factory," rather Chinese innovation, or "innovation with Chinese characteristics" explores the unique learning strategies adopted by Chinese firms.

According to the innovative manufacturing perspective advanced by (Nahm and Steinfeld, 2012), the accumulation of diverse, firm-specific know-how is a central component to China's competitive specialization in manufacturing. This firm-specific knowledge, combined with the ability to access foreign technology and, subsequently employ backward design strategies, enables Chinese firms to re-create 'imitated' products at a cheaper cost, crowding out foreign suppliers (Nahm and Steinfeld, 2012). Although products can be made cheaper in other developing countries, multi-national firms choose China for more than just its cheap labor costs and emerging consumer market, but also because of its engineering capabilities and quick tempo to re-orient a product for large-scale production with the lowest cost possible.

The 2011 U.S.-China Economic and Security Review Commission Report confirms that Chinese innovation has made substantial in-roads in a relatively short period of time, expanding into everything from design, to genuine innovation, development and commercialization of new products and processes. Based on this report, Nahm and Steinfeld (2012) argue that China's place within global manufacturing is enabling it to develop the propriety know-how beyond manufacturing. In effect, Chinese firms are doing things differently than pioneer firms from developed countries, which leads to different learning outcomes, and as pointed out in Hall (1995), this type of imitator strategy leads the imitator firms to become, in essence, innovators in their own way.

The innovative manufacturing perspective complements arguments made by some China scholars who claim that China's learning process model of development is unique, deviating from that of other transitioning countries such as South Korea, Taiwan, Hong Kong and Singapore (Qian and Xu, 1993; Chen and Qu, 2003). For example, Chen and Qu (2003) argue that Chinese firms integrate operational, tactical and strategic learning, amalgamating to produce a specific form of technological learning that differs from other newly industrializing economies (NIEs). Aware of such accounts, the subsequent analyses adopted in this dissertation take into consideration the necessary contextualized knowledge regarding China's spatial, institutional and organizational features to explain its unprecedented growth.

1.3 Objectives

The key objective of this dissertation is to examine the direct and indirect effects of industrial policy, innovation and agglomeration on firm performance. How does firm innovation and state-intervention influence firm performance and survival? How do the effects of agglomeration economies influence firm performance and are these agglomeration effects influenced by state policy? To answer these questions, I first examine the respective agglomeration- and innovation-firm performance relationships taking into account policy distortions, and then develop and introduce a new structural model approach that integrates cross-scalar firm-environment interactions with technological learning and knowledge spillovers into an innovation-agglomeration-performance framework.

Specifically, I adopt three econometric strategies to statistically: 1) assess the role of Chinese innovation, policy and agglomeration on new firm survival; 2) disentangle true agglomeration effects on firm performance from spatial sorting and firm selection in the presence of policy distortions; and 3) examine the sources of technological learning and the effects of firm-environment cross-scalar interactions on the innovation process and firm performance. I pay careful attention to the endogeneity issues that typically arise when trying to estimate the respective effects of innovation and agglomeration on firm performance.

Another primary objective is to estimate the short- and long-run effects of policy on firm performance, as well as allow for the heterogeneous impacts of protectionism to vary according to spatial scale (i.e. at the direct, local and state levels). The issue of scale is important in the context of China's policy interventions. As a result of China's ongoing transition, and resulting administrative decentralization, provincial and local authorities have increasingly implemented policies to protect firms operating within their locale. Along with greater decision-making powers to develop local economies (Wei, 2000), decentralization has, in turn, resulted in intense interregional competition and new forms of local protectionism (He, 2009). As a result of China's decentralization, the state can no longer be viewed as an unitary actor working in unison across cities and provinces within China; directives from the center are frequently ignored or reformulated to produce greater local benefits. In each of the econometric approaches employed in this dissertation, distinctions are made between state industrial protectionist policy and regional projectionist policy to allow heterogenous policy distortions in the economy.

1.4 Contributions to the Literature

Among the major contributions to the literature is the adaptation of conceptual and methodological frameworks, largely developed and applied within advanced economy contexts, to suit the contextual realities of doing work on China, a transitioning and dirigiste economy. To date, comparatively few analyses link agglomeration, innovation and policy to firm performance in a transitional economy context with imperfect markets and a strong state-presence; rather empirical works remain largely confined to advanced, Western countries. Findings from advanced capitalist economies, however, may be highly country-specific due to varying institutional organization, and are therefore not necessarily generalizable to transitioning economies (Falck, 2007). Moreover, transitioning economies, by definition, undergo substantial changes in their political, economic and legal institutions, which present new opportunities and challenges to enterprises that are not present in advanced, Western countries

(Child and Tse, 2001). As a result of their exclusion, the determinants of firm performance in transitioning economies are not well understood (Deshpande and Farley, 2000).

1.4.1 Contributions to 'New 'New' Economic Geography' and Public Policy

Despite a longstanding literature that positively links agglomeration economies to innovation and economic growth (Porter, 1990; Fujita and Thisse, 2003; Henderson, 2003, 2005; Acs et al., 2007; Glaeser, 2008; Baldwin et al., 2008), the empirical literature on the agglomeration-firm productivity relationship remains undetermined (Antonietti and Cainelli, 2011). While the brunt of research confirms the positive effects of agglomeration economies on firm productivity (Segal, 1976; Ciccone and Hall, 1996; Henderson, 2003; Brülhart and Mathys, 2008; Rigby and Brown, 2013), some recent studies find that agglomerations may harm firm performance in certain settings (Shaver and Flyer, 2000; Arikan and Schilling, 2011; Oort et al., 2012).

Coinciding with the emergence of the NNEG (Ottaviano, 2011), the introduction of heterogeneous firm models has led to somewhat of a resurgence of research that promises to offer new insights into the effects of agglomeration on firm productivity (Baldwin and Okubo, 2006; Venables, 2011; Behrens and Duranton, 2010; Combes et al., 2012). Based on this line of research, the new agglomeration literature identifies spatial sorting and firm selection as two alternative explanations to urban increasing returns that may explain the empirically observed urban premium – firms produce more in agglomerative regions than firms located elsewhere.

While this new agglomeration literature treats the endogeneity issues that typically arise when trying to estimate the effects of agglomeration on firm production, they are specifically applied to advanced capitalist economies with mature markets, operating under the following assumptions: factors move freely across cities, no barriers to entry or exit, and limited government intervention. Such assumptions, however, are not valid when applied to the context of transitioning economies, especially China, where economic, and in particular, industrial policy remain largely responsible for steering the location, direction and intensity of the production of goods (Thomas, 2011).

The role of public policy, therefore, and how it influences agglomeration and firm performance becomes paramount in the context of studying transitioning economies like China. The linkages between public policy and agglomeration is an increasingly studied topic, and was first developed in a series of papers that examine the role of agglomeration rents on regional tax competition (Kind et al., 2000; Ludema and Wooton, 2000; Baldwin and Krugman, 2004). In this line of research, the direct effects of policy on agglomeration are elaborated, yet, many questions remain understudied: how does policy mediate the agglomeration-firm performance relationship? How does policy impact the processes of firm selection and spatial sorting?

Part of this dissertation (Chapter 5), therefore, contributes to the literature by bridging advancements made in 'new 'new' economic geography' with the emergent literature on public policies' effects on agglomeration and firm performance. To link these bodies of literature, my empirical study simultaneously addresses three issues that up until now have generally been considered separately. First, I identify competing sources of productivity advantages found in firms located in more agglomerated cities, disentangling the true agglomeration effects from that of spatial sorting and firm selection. Second, firm heterogeneity based on firms' political connections are directly incorporated into my modeling approach, enabling us to estimate the relationship between policy and firm performance. Lastly, I investigate whether the mediating effects of state-protectionist policies distort the inter-related processes of agglomeration, sorting and selection.

1.4.2 Contribution to 'Geo-Economics of Innovation'

In the empirical literature, few studies offer representative analyses into the process of Chinese innovation and its impact on firm performance. Some relevant studies have begun to emerge in the English and Chinese language literatures that investigate the role of innovation on firm survival and success (Naidoo, 2010; Guan et al., 2009; Zhou, 2006; Tan, 2001). While these studies largely confirm a positive relationship between innovation and firm success, they tend to be small, cross-sectional case studies carried out in select cities. As a result, their findings are not necessarily generalizable across all Chinese cities or industries.

The final contribution of this dissertation (Chapter 6) attempts to add geographical features into the conventional economics of innovation literature. I develop a structural model of innovation (CDM) following the seminal work by (Crépon et al., 1998) that incorporates and models localized geographical spillovers at each stage of the model. My structural model is further set apart from previous structural approaches by its theorization and subsequent empirical analysis of a complex set of direct and indirect cross-scalar effects that attempt to disentangle the sources of technological learning and knowledge spillovers.

To disentangle the various sources of technological learning, I identify multiple cross-scalar learning interaction effects that take place: (1) within the firm (learning by doing), (2) between the firm and the environment (learning by exporting; and a firm's absorptive capacity to acquire intra- and inter-industry learning spillovers), and (3) external to the firm (intra- and inter-industrial learning spillovers mediated by institutions). These direct and mediating effects of learning and knowledge spillovers are found to be important determinants of the innovation process and firm performance, albeit their respective impacts vary depending on both the different types of interactions, as well as the stage of innovation under examination.

1.5 Dissertation Road Map

This section provides a chapter breakdown for the remainder of the dissertation. Chapter 2 provide the theoretical framework of the dissertation, followed by an introduction to the data and key variables in Chapter 3. Chapters 4-6 provide the empirical portion of the dissertation and Chapter 7 concludes. With regards to the three empirical chapters, the appropriate research questions, as well as corresponding findings and the implications are succinctly provided.

Chapter 2

In Chapter 2, I discuss the relevant literature and outline my theoretical framework. In the first two sections, I respectively discuss the relevant literature on the innovation- and agglomeration-performance relationships. The subsequent section integrates both bodies of literature into a cross-scalar firm-environment structural model approach that introduces technological learning and knowledge spillovers into a conventional innovation-agglomeration-performance framework.

Chapter 3

In Chapter 3, I introduce the data and operationalize my variables. I describe the development of my proxies for firm performance, innovation, learning, agglomeration and policy, among others. Data limitations and issues with variable measurement are also discussed.

Chapter 4

Chapter 4 presents my first empirical chapter and examines the relationship among policy, innovation, agglomeration and firm performance. I use new firm survival as a proxy for firm performance and estimate several accelerated failure time (AFT) hazard models, controlling for various firm, spatial and industrial covariates. The main questions I seek to answer are: (i) What are the main determinants of new firm survival in China? (ii)How does state industrial policy and/or local protectionism mediate the relationship between innovation and firm survival? (iii) Based on the statistical evidence, does state protectionism likely increase or diminish the risks associated with pursuing innovation?

The main findings generated from my analysis include the following. Firms engaged in innovative activities enjoy significantly higher rates of survival compared to non-innovative firms. Direct, local and state protectionism increase the chances of firm survival for all firms in the short-run. Lastly, only direct subsidies positively mediate the innovation-survival relationship, whereas both local and state protectionism are found to harm the survival rates of innovative firms in the long-run.

These findings point to progressive steps made by China as a result of its ongoing transition from a command economy to a market-led economy. Similar to the findings in Western, advanced capitalist countries, innovation directly increase a firm's survival chances. I also find that state- and local-intervention can harm survival rates for innovative firms in the long-run, thereby suggesting that the riskiness associated with pursuing innovative activities increases in the presence of prolonged state-protectionism. Consequently, efforts should be made to gradually reduce the level of state-intervention.

Chapter 5

Chapter 5 focuses on the effects of agglomeration on firm performance, accounting for endogeneity issues and policy distortions. I introduce a new fixed effects penalized quantile regression model to disentangle the effects of true agglomeration economies from that of spatial sorting and firm selection for three specific industries: agro-food industry, textiles and electronics. The main questions I seek to answer are: (i) Are there observable productivity advantages for firms located within agglomerations and is the agglomeration-performance relationship sensitive to specific industries? (ii) Does spatial sorting and firm selection account for the positive agglomeration-performance relationship? (iii) Does state-intervention distort the processes of agglomeration, spatial sorting or firm selection?

The main findings from the analysis are as follows. Urbanization economies are found to exist in all three industries of analysis: the agro-food processing, textiles and electronics industries. Firms in textiles and electronics also enjoy the advantages generated from industrial specialization. In the agro-food processing industry, neither agglomeration economies nor spatial sorting or firm selection are very apparent. In the textiles industry, evidence suggests that spatial sorting of firms explains some of the productivity advantages of being located in denser regions. In the electronics industry, a strong selection effect is found to explain some of the productivity advantages of firms located in denser regions.

State-intervention harms low-productivity, subsidized firms in the agro-food industry, and harms both low- and high-productivity firms in the textiles industry. State-protectionism in the electronics industry effectively mitigates the selection effect on subsidized firms, although only the high-productivity subsidized firms are able to absorb the knowledge spillovers.

The main implications of these findings suggest that the benefits of knowledge spillovers and the extent of firm selection and spatial sorting are industry specific. Similarly, the degree and effectiveness of state-protectionist policy to sort firms and circumvent the selection effects is also industry specific. The presence of prolonged state-intervention generates a new source of instability, as protectionism tends to disproportionately favor high-productivity firms, at least in certain industries, thereby exacerbating intra-industrial firm inequality.

Chapter 6

Chapter 6 takes into account the endogeneity issues related to measuring the effect of innovation on firm performance by building a structural model of innovation. I develop a structural model based on 3-staged least squares (instrument variable) with fixed effects to simultaneously estimate a set of recursive equations that correspond to the entire process of innovation and its effect on firm performance. A set of learning interaction terms and knowledge spillover proxies are integrated into the model and efforts are made to examine their respective impacts at each stage of the innovation process and on firm performance. I attempt to answer the following set of questions: (i) What factors influence a firm's (i) decision to innovate; (ii) innovation intensity; (iii) innovation output; and (iv) performance? (ii) What sources of technological learning impact Chinese indigenous innovation and how does a firm's absorptive capacity facilitate the learning process? (iii) What role does external knowledge inputs (knowledge spillovers) play in the knowledge production function and firm performance? (iv) How does state industrial policy and/or local protectionism directly and indirectly affect the innovation process and firm performance? (v) How does institutional capacity mediate the effect of knowledge spillovers on the innovation process and firm performance?

The main findings generated from my analysis are as follows. Firms that engage in indigenous research and development increase their innovative throughput, which in turn, is found to increase firm performance. Firms are found to benefit from learning by doing at each stage of the model; conversely no evidence to suggest that firms learn by exporting. In the early stages of innovation, there is no evidence to suggest that Chinese firms are capturing learning spillovers and incorporating them into their innovation effort, even when the firm's absorptive capacity is taken into account. In the later stages of innovation, learning spillovers are found to positively increase the firm's innovation output, as well as its performance, especially for firms with high absorptive capacity.

Interventionist policies encourage firms to pursue an innovative strategy, however, in the later stages of the innovation process the same protectionist policies lead to unwanted consequences that tend to hurt the overall innovation climate and diminish firm performance. Lastly, institutional capacity positively facilitates the ease with which tacit knowledge generated from the external environment is captured by the firm and incorporated into its knowledge production function.

The implications of these findings highlight the positive role of innovation, even when controlling for endogeneity, on firm performance, revealing that the returns to innovation in a developing and dirigiste economy are similar to those in advanced market economies. Due to China's transitional stage of development, firms do not yet have the absorptive capacity to incorporate external knowledge inputs into the early stages of innovation, which impedes genuine innovations from occurring. In the long-run, state interventionist policy will hinder China's progress in innovation. One way to reduce the reliance of firms on state-protectionism is to develop institutional norms and rule of law, which may substitute the need for strong state intervention and, in turn, spur innovation as China conforms to the logic of the market.

Chapter 7

Chapter 7 provides a general conclusion of the main findings. The concluding remarks attempt to streamline the diverse set of contributions produced from the empirical approaches into a unified policy-relevant framework. In general, the empirical findings reflect the bipartite system in China that is characterized by dual, self-reinforcing market-led principles occurring in tandem with state directives. Evidence suggests that China's transition towards a market-oriented economy has firmly taken root, creating in some respects, similar firm dynamics as those operating in other countries.

As China continues to emphasize the development of its "national champions", regional and industrial policy needs to balance the necessity of protecting key nascent industries, while at the same time fostering strong competitive environments that allow firms to flourish. Persistent, high levels of state-protectionism, however, create economic imbalances that disproportionately harm low-productivity firms in some cases, while also, somewhat perversely, prevent them from exiting the market. This, in turn, leads to inefficient and non-competitive markets that diminish overall returns to innovation and harm firm performance.

Building a solid institutional environment will reduce the high risks associated with pursuing innovation and will help facilitate the transferring of tacit knowledge leading to both intra- and inter-industrial spillovers, thereby reducing firm dependency on state protectionism, and spurring firm competitiveness. Strong institutions, combined with limited, strategic policy instruments, will enable Chinese firms to better absorb learning spillovers and integrate them with in-house R&D activities. In time, it is likely that China will continue to contribute widely to the global stock of knowledge and increase its value-added at all points of the global production chain.

CHAPTER 2

Literature Review and Theoretical Framework

2.1 Innovation, Policy and Firm Performance

Innovation is noted as being at the heart of economic growth, and it is well known that innovation is essential for firms to maintain a competitive advantage in the market (Porter, 1990; Bruderl et al., 1992; Wagner, 1999) and to achieve long-term success and survival (Schumpeter, 1942; Berthon et al., 1999; Noble et al., 2002). In the literature, three dominant strands of research have emerged focusing on different aspects of the innovation process: (i) the innovation-performance (survival) relationship, (ii) the knowledge production function, and (iii) the structural framework that links knowledge production to firm performance.

The first strand has led to a general consensus that the role of innovation enhances firm performance, including survival (Griliches, 1958; Wakelin, 2001; Wang and Tsai, 2003; Griffith et al., 2004). For instance, Esteve-Perez et al. (2004) analyze Spanish manufacturing firms and find that innovation increases the chances of firm survival. Using a large, representative sample of Australian firms from 1997-2003, Jensen et al. (2008) find that trade marking increases survival rates of new firms. Cefis and Marsilli (2005, 2006) divide Dutch firms operating during the time period 1996-2003 into innovating and non-innovating, and find that small, innovating firms experience longer life expectancies. Similarly, Baldwin et al. (1994) find that innovation is a key determinant of firm survival and success in Canada.

The second strand of innovation research has developed largely out of the seminal paper written by Pakes and Griliches (1980). The authors ascribe the positive association between innovative inputs (R&D activities) and innovative output (patent activities) as the "knowledge production function." A slew of subsequent works has emerged linking innovative inputs to innovative outputs (Cohen and Levinthal, 1989, 1990; Anselin et al., 1997, 2000; Zahra and George, 2002; Acs, 2002; Roper et al., 2008; Love and Roper, 2009).

In the third strand, Crépon et al. (1998) extend the knowledge production framework developed in Pakes and Griliches (1980), embedding it into a recursive system of equations that links the knowledge production function to firm performance (referred to as CDM framework). The structural model has become a popular approach to examine the linkages between innovation and firm performance[1]. The main advantages of the CDM framework over previous approaches, is that it corrects for the undesirable effects produced by selectivity and simultaneity bias (Lööf and Heshmati, 2006); moreover, it is parsimonious and empirically tractable (Griffith et al., 2006).

In the innovation literature on China, relevant studies have begun to emerge in the English and Chinese languages that investigate the role of innovation on firm survival and success (Tan, 2001; Sun, 2002; Naidoo, 2010; Guan et al., 2009; Zhou, 2006; Wang and Lin, 2013). In one case, Naidoo (2010) analyzes survey data from 184 small-to-medium enterprises located in the industrial textile clusters along coastal provinces and finds firms that developed and implemented an innovation strategy were able to maintain a competitive market advantage,which in turn, led to a higher likelihood of survival during times of crisis. Relying on a sample of 300 firms from three large cities in China, Zhou (2006) finds that pursuing an innovative strategy, as opposed to imitation, plays a paramount role in firm success. Zhou and Zeng (2011) use panel data for Chinese listed companies from 2002 -2009 and find that R&D investment in both capital and personnel results in a positive corporate financial performance.

Most of the empirical works on China largely confirm the positive role of innovation, and the significance of location and policy instruments, in enhancing firm performance. However, the brunt of these empirical works fall into either the first or second strand of the innovation literature, thereby restricting the investigation to studying separately the knowledge production function from its impact on firm performance (for the only exception, see Jefferson et al. (2002)).

2.1.1 Returns to Innovation with Policy Distortions

Coinciding with China's opening up strategy and process of internationalization, Chinese enterprises have become exposed to large amounts of foreign capital, reorienting them to-

[1]see Jefferson et al. (2002); Kemp et al. (2003); Lööf and Heshmati (2006); Griffith et al. (2006); Arvanitis (2006); Miguel Benavente (2006); Johansson and Lööf (2009); Iraj Hashi & Nebojsa Stojcic (2010); Antonietti and Cainelli (2011).

wards an export-based development strategy. China's new private firms simultaneously face increasingly intense competition from foreign competitors. The increasing competition from China's opening up strategy has urged the Chinese authorities to focus on promoting indigenous innovation through strong state interventionist policies.

For instance, then Premier Wen Jiabao delivered a speech in 2006 emphasizing the two main drivers for China's continued progress and development include the persistence to promote opening and reform, and to "rely on the progress of science and technology and the strengths of innovation." In the same year, the promotion of innovation received center stage in China's National Medium- and Long-Term Plan for the Development of Science and Technology (2006- 2020) (Liu et al., 2011). The plan unveiled the "blueprint" for innovation that will bring about the "great renaissance of the Chinese nation," with stated goals to transform China into a technology powerhouse by 2020 and a global leader by 2050.

The policy, legal and institutional environment is important for innovation because investing in innovation is inherently risky and, in theory, can enhance firm performance or lead to financial distress and failure (Buddelmeyer et al., 2010). Compared to advanced, capitalist economies, the risk of engaging in innovative activities is comparatively high in China due to widespread intellectual property theft, unlawful abrogation of legal contracts and unfair competitive practices, the shortage of venture capital, poor institutional protection, and insufficient market demand (Guo, 1997; Sun, 2002; Wang and Lin, 2008; Zhou, 2008). These barriers not only increase the risk of innovation, but also diminish incentives for Chinese firms to pursue indigenous innovation activities engendered from purely domestic inputs. As a result of the poor innovation climate and increasing global competition, many of China's innovative firms must depend heavily on both state intervention and local protectionism in order to survive (Li and Atuahene-Gime, 2001).

While government involvement in the economy is critical for every country, the degree and nature of healthy state involvement is subject to widespread debate (Huang et al., 1999). In some situations strong protectionist policy can lead to positive outcomes, at least in the short term. For instance, policy instruments, via state subsidies or local preferential tax breaks, play a positive role in insulating firms from foreign competition, as well as creating demand for technological learning and increasing the supply of technological capability (Lall, 1992).

Some recent empirical studies reflect this view and show that protectionist policy positively mediates the innovation-performance relationship in the short term. In one study, Guan et al. (2009) collected data for 1,244 firms in Beijing and found that innovative firms that received government subsidies, via the government's high-tech firm accreditation system, generally performed better relative to unsubsidized firms. In their cross-sectional study of Chinese listed companies, Xie et al. (2009) demonstrate a positive relationship between state subsidies and innovation activities, i.e. R&D expenditures and performance. In a sectoral analysis, He and Qing (2011) find that policy mechanisms directly impact the performance of industrial catch-up for private Chinese firms in the telecommunication and automobile industries.

Conversely, the inherent riskiness of innovation in the long-term may increase if the returns to innovation are undermined by state industrial policy and protectionism (Park and Luo, 2001). This is because protected firms maintain a close relationship to the state and have unfettered access to state finance with little to no state oversight (Huang, 2003), engendering a world of survival certainty. Since these protected firms are insulated from outside competition, they are deprived of the incentives to innovate and upgrade their technological systems (Fuller, 2008). As a result, inefficient state-favored firms are propped up, and prevented from exiting the market, much in the same manner as state-owned enterprises. The results of such protectionist policies will lead to a non-competitive environment and diminished innovation and firm output (Carlin et al., 2004).

2.2 Agglomeration, Policy and Firm Performance

The spatial concentration of economic activity has led to profound transformations in the global geo-economic landscape in recent history. The co-location of firms and emergence of industrial clusters are believed to be essential aspects of the learning process and generation of knowledge (learning) spillovers, which in turn fosters growth, innovation and productivity

(Porter, 1990; Fujita and Thisse, 2003; Henderson, 2003, 2005; Acs et al., 2007; Rodriguez-Pose and Crescenzi, 2008; Glaeser, 2008; Baldwin et al., 2008; Kesidou and Romijn, 2008; He, 2009).

The literature discerns two types of externalities. Within- industry knowledge spillovers results from the spatial concentration of firms in the same industry, leading to localization economies, while the increased diversity of economic activity within a region leads to urbanization economies. Although a large literature exists that positively links agglomeration economies to innovation and economic growth, the empirical literature on the agglomeration-firm productivity relationship remains undetermined (Antonietti and Cainelli, 2011). Some studies confirm the positive effects of agglomeration economies on firm productivity (Segal, 1976; Ciccone and Hall, 1996; Henderson, 2003; Brülhart and Mathys, 2008; Baldwin et al., 2010; Rigby and Brown, 2013), while other studies find that agglomerations harm firm performance (Shaver and Flyer, 2000; Arikan and Schilling, 2011; Oort et al., 2012).

Under the 'new 'new' economic geography' framework, the issues of firm heterogeneity and endogeneity play a central role in the new agglomeration literature. Firms are no longer treated as being identical to one another, as was the case in earlier agglomeration works (Glaeser et al., 1992; Ciccone and Hall, 1996; Rigby and Essletzbichler, 2002; Henderson, 2003)[2]; rather, different firm attributes lead to different outcomes. The new agglomeration literature is interested in distinguishing between true agglomeration effects from that of spatial sorting and firm selection. Sorting induces selection, and either process, either independently or coupled together, can lead to an empirically observable higher aggregate firm output in agglomerated regions, even in the absence of genuine positive spatial externalities.

Integrating Krugman (1991) with Melitz's heterogeneous firm model (Melitz, 2003), the seminal work by Baldwin and Okubo (2006) reveals that higher productivity firms locate within more agglomerated regions (sorting effect), thereby increasing local competition. Subsequently, lower-productivity firms are unable to pay increasing prices and are forced out of the market (selection effect). In another prominent study, Combes et al. (2012) apply a

[2]See Rosenthal and Strange (2004) for a comprehensive overview of the early agglomeration literature that predates the emergence of the 'new 'new' economic geography'.

quantile regression approach to French firm-level data to distinguish between urbanization economies and firm selection. Findings show that the productivity advantage of firms in agglomerated regions is indeed explained by agglomeration effects.

In their analysis of Japan's silk-reeling industry, Arimoto et al. (2012) distinguishes between localization economies and selection effects by comparing the productivity distribution within and outside industrial clusters. Results reveal a rightward shift in the distribution of firms located within clusters, indicating that genuine agglomeration effects are responsible for increased firm productivity in concentrated regions. Behrens and Duranton (2010) offer the first attempt to distinguish agglomeration economies from both spatial sorting and selection using quantile regression techniques. The authors find evidence for agglomeration economies, while noting that both selection and spatial sorting are prominent features found in U.S. cities.

The study of agglomeration has received considerable attention in the Chinese literature and has been used to assess the impacts of spatial concentration on firm productivity (He and Wang, 2012; Lin et al., 2011) and regional development (Batisse, 2002; Fan and Scott, 2003; Gao, 2004; He and Pan, 2009). Fan and Scott (2003) using location quotients, find a positive relationship between agglomeration and city growth, particularly for liberalized industries. He and Pan (2009) find industrial specialization and local competition positively impact economic growth, although these effects are found to be non-linear. On the other hand, both Batisse (2002) and Gao (2004) find that both industrial specialization and diversity are negatively associated to economic growth at the provincial level.

At the firm-level, He and Wang (2012) find that enterprises in general benefit from agglomeration economies, although the effects are found to differ across regions and sectors. Lin et al. (2011) specifically examine the textiles industry. The authors find a U-shaped relationship between spatial concentration and firm-level productivity growth. Wei and Liu (2006) find several transmission mechanisms by which agglomeration generates knowledge spillovers, thereby benefiting firm productivity. The authors show that the concentration of R&D and exports generate positive inter-industry productivity spillovers, and the concentration of FDI generates both intra- and inter-industry spillovers for indigenous Chinese firms.

2.2.1 Returns to Agglomeration with Policy Distortions

It is well-known that state institutions and policies can lead to distortions in the economy, both in terms of patterns of agglomeration and firm performance. Recent works examine how policy distortions directly affect agglomeration. Research shows that agglomeration can be fostered by imperfect labor markets (Egger and Seidel, 2008), financial market development (Seidel and von Ehrlich, 2011) and uncoordinated regional competition (Fenge et al., 2009). For instance, in Seidel and von Ehrlich (2011), low-productivity firms are found to be precluded from external finance leading to their exit from the market. In this case, the authors show that policy may reinforce selection effects by expediting the process by which low-productivity firms choose to exit the market due to their inability to obtain outside loans.

Conversely, agglomeration may be prevented by regional infrastructure-based federal subsidies (Martin and Rogers, 1995) and anti-agglomeration subsidies (Okubo, 2012). In Okubo (2012), the authors show that low-productivity firms are most likely to take the relocation subsidy. Under certain conditions, however, high-productivity firms will be induced to relocate to the periphery if the relocation subsidy is proportionate to the profits. This finding demonstrates that policy can potentially distort both selection and spatial sorting. The anti-agglomeration subsidy would enhance the selection effect when low-productivity firms are incentivized to re-locate outside agglomerations, whereas the same relocation subsidy would also lead to spatial sorting effects if the high-productivity firm relocates to an emerging cluster in the periphery.

In addition to affecting the agglomeration of industrial activity, state policies can also generate economic distortions that directly affect firm performance. Certain policies result in resource mis-allocation (Hsieh and Klenow, 2009), which in turn, has been shown to have important effects on firm performance (Sun and Zhang, 2012). For instance, Restuccia and Rogerson (2008) examine firms' political connections to the state. The author find that policies that levy plant-level taxes or subsidies on firms, assumed to have identical technologies, can result in resource mis-allocation and reduce aggregate TFP in the range of 30-50%. Conversely, as previously discussed, policy instruments may lead to positive outcomes on firm performance by insulating domestic firms from foreign competition, as well as by creating demand for technological learning and increasing the supply of technological capability (Lall, 1992).

2.3 A New Geo-Economic Structural Approach: Integrating Technological Learning and Knowledge Spillovers into the Innovation-Agglomeration-Performance Framework

Building on the public policy, innovation- and agglomeration-performance literatures (discussed above), the remainder of the chapter introduces a new structural framework that attempts to link the literatures. The structural approach incorporates cross-scalar firm-environment interactions to study the innovation-agglomeration-performance relationship taking into account technological learning, knowledge spillovers and policy distortions.

Following in the spirit of Crépon et al. (1998), the baseline structural model of innovation includes the following four main equations. Equation (i) is the firm's decision to engage in innovation, determined by a positive value for R&D expenditure. Equation (ii) is the intensity of the firm's R&D effort, and equation (iii) is the knowledge production function based on the intensity of new product or process sales. Equation (iv) is the performance equation, where knowledge is an input for a firm's total factor productivity (TFP).

Adding to the baseline model, I incorporate multiple sources of technological learning, knowledge spillovers and institutional capacity (See Figure 2.1). To disentangle the various sources of technological learning, I identify multiple cross-scalar learning interaction effects that take place: (1) within the firm (learning by doing), (2) between the firm and the environment (learning by exporting; and a firm's absorptive capacity to acquire intra- and inter-industry learning spillovers), and (3) external to the firm (intra- and inter-industrial learning spillovers mediated by institutions).

Three sets of learning interactions take place that account for learning by doing (D_i), learning by exporting (E_i) and absorptive capacity to utilize foreign knowledge inputs (S_i), and the effect of mediating institutions (I_i). Both S_i and I_i include two learning spillover terms, one for intra-industry spillovers and another for inter-industry spillovers. In total, the model takes into account six learning interaction effects.

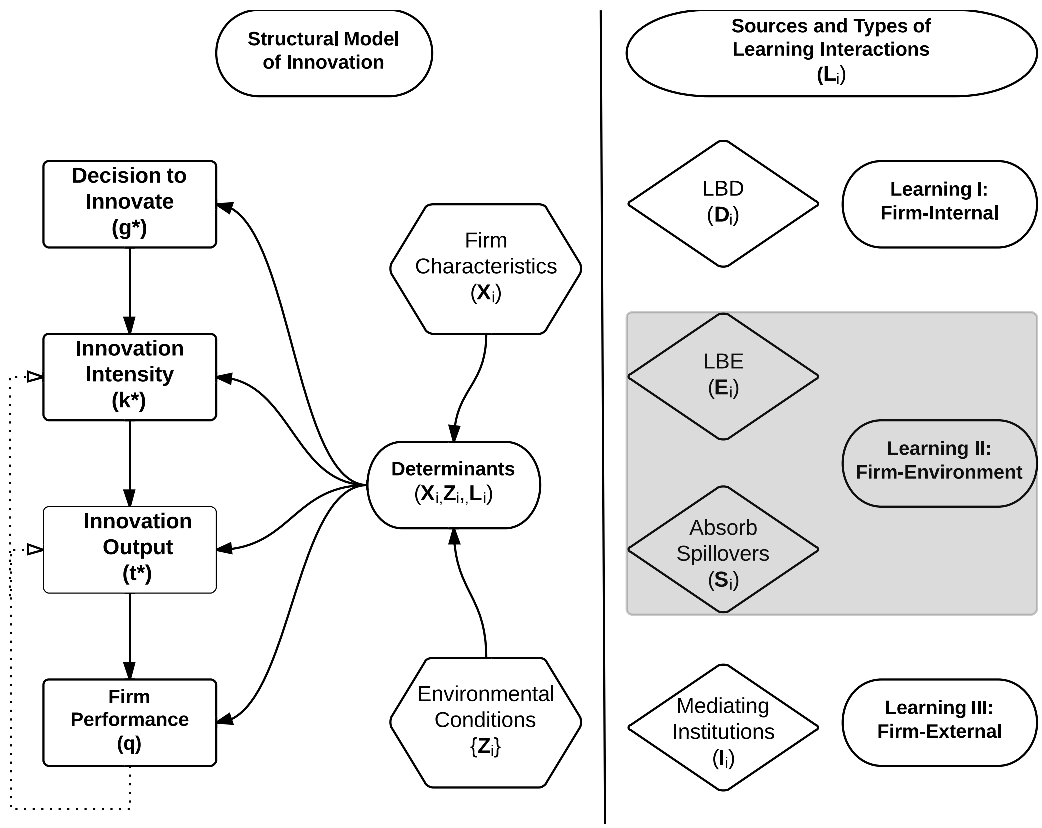

Figure 2.1: Augmented Structural Model of Innovation with Learning Interactions and Knowledge Spillovers

2.3.1 Technological Learning and Absorptive Capacity

Technological learning is defined as the process of building and accumulating technological capability: the ability to effectively use technological knowledge in production, engineering and innovation to become competitive in the marketplace (Kim, 2001). The learning ability

– absorptive capacity – of the firm becomes especially critical in the ability of the firm to capture and incorporate external knowledge inputs into its production function (Zahra and George, 2002). According to Cohen and Levinthal (1990), "The premise of the notion of absorptive capacity is that the organization needs prior related knowledge to assimilate and use new knowledge." Geroski et al. (1993) highlight the importance of not only innovation in itself, but also the learning process that takes place as a firm engages in innovative activities.

Several potential sources have been identified in the literature that can facilitate a firm's learning process, which in turn can influence the process of innovation and firm performance. Pertinent to the scope of this dissertation, I identify the following sources of learning grouped into three categories: learning internal to the firm (learning by doing), firm-environment learning interaction (export by doing and absorptive capacity of the firm mediated by learning spillovers) and learning external to the firm (learning spillovers mediated by institutions).

2.3.2 Learning I: Internal to the Firm

Learning by doing (LBD) is the process by where the accumulation of production experience leads to increased performance and growth. The literature distinguishes between passive and active learning, with the former suggesting that LBD is an incidental and costless by-product of the firm's production activities, and the latter occurring as the result of intentional activities of the firm to increase organizational know-how, such as R&D investments (Thompson, 2009). Early studies by Rapping (1965) and Sheshinski (1967) find evidence for significant learning effects as firms accumulate experience. Similarly, research confirms the positive and significant role of active learning, based on R&D investments, on firm performance (Jovanovic, 1982; Pakes and Ericson, 1998; Liu and Buck, 2007).

2.3.3 Learning II: Firm-Environment Learning

In addition to LBD, the geographical environment is a potentially important source of supplemental knowledge generated external to the firm (Lööf and Nabavi, 2013). Two main sources of firm-environment learning interactions are: Learning by exporting (LBE) and absorptive capability of the firm to capture learning spillovers.

2.3.3.1 Learning By Exporting

LBE occurs as exporting firms benefit from their foreign buyers' technical and managerial expertise or the expertise from other foreign contacts, such as competitors, suppliers or scientific agents (Rhee et al., 1984; Clerides et al., 1998; Silva et al., 2012). In addition, foreign buyers apply pressure for exporters to produce cheaper, yet higher quality products, which generates incentives for the exporting firm to become more efficient (Evenson and Westphal, 1995). The accumulation of external knowledge inputs by exporting firms is not available to firms confined to the domestic market. This difference in access to external knowledge is thought to be a key factor that explains why exporting firms tend to be more productive than non-exporters, although the direction of causality between exports and productivity is debatable (Balasubramanayam et al., 1996). Despite the existence of anecdotal evidence purporting the significance of LBE, the econometric evidence so far provides little support (Salomon and Shaver, 2005).

2.3.3.2 Geography of Knowledge Spillovers

Learning spillovers occur when the firm is able to incorporate external knowledge inputs into its knowledge production function. Research based on the initial works of Cohen and Levinthal (1989, 1990) agree that the production of innovation and new technological knowledge increasingly depends on the firm's ability to search the external environment to access complementary knowledge inputs. According to Keller (2010), the benefits derived from learning spillovers in urban regions can be as large as the return from firms own investments.

On the one hand, learning spillovers are advantageous because they enable the firm to overcome the financial and technological limitations of attempting to produce new knowledge solely based on in-house innovation (Antonellia et al., 2011). At the same time, learning spillovers may cannibalize some of the benefits normally generated from the LBD process.

As a greater stock of knowledge generated external to the firm becomes freely available, the firm may avoid investing in learning opportunities, such as in-house R&D, as a cost- saving strategy (Ghemawat and Spence, 1985; Barrios and Strobl, 2004).

Several studies from developed countries find that learning spillovers result in positive firm performance (Thornton and Thompson, 2001; Gruber, 1998). In a study on Spain, Barrios and Strobl (2004) find that both firm-level LBD and learning spillovers positively influenced firm performance. It is perhaps even more important to disentangle the sources of learning internal to the firm and between the firm and environment in developing countries, since these firms are much more likely to rely solely on learning spillovers in lieu of carrying out in-house RD.

2.3.4 Learning III: External to the Firm

As discussed above, the legal and institutional environment is also likely to directly impact both the innovation process (Li and Atuahene-Gime, 2001) and helps to conceptualize the dynamic interplay between actors (firms) and structures (Geels, 2004). Building stable institutions can also mitigate certain risks associated with pursuing innovation, whereas low state- capacity leads to unclear rules, distrust and rent-seeking activities, all of which impinge upon the capacity and inclination of the firm to innovate (Steinfeld, 2004b).

Besides the direct effects, the mediating impact of institutions on learning spillovers are expected to influence the ease at which tacit knowledge can be transmitted at the organizational or industrial level. These expectations of institutions are in line with previous research that contends that the effects of innovation on firm performance and economic growth cannot be fully understood without considering the social and institutional conditions in an economy (Rodriguez-Pose and Crescenzi, 2008).

2.3.5 Conclusion

The theoretical discussion within this chapter lays the foundation for the subsequent empirical work to be undertaken for the remainder of this dissertation. To summarize, this chapter draws upon and integrates theories emanating from the innovation, economic geography and public policy literatures together into a unified framework. One of the main features of my analytical framework allows for cross-scalar interactions to take place among firm characteristics, policy instruments and spatial variables in order to reveal new insights into the innovation process and firm performance in China. In the following section, I will discuss the data source and variable development.

CHAPTER 3

Methodology

3.1 Data Description

My empirical analyses utilize the Annual Survey of Industrial Firms (ASIF) compiled by the National Statistical Bureau of China for the years 1998-2007. Included in the data are all firms with an annual turnover over five million Renminbi, approximately $600,000, accounting for 95% of industrial output in China (Brandt et al., 2012). An extensive set of firm characteristics are included in the database, including information on firm ownership structure, total sales, gross output, employment, geographic location, industry affiliation, new product or process sales and sources of finance[1].

Despite the unusually rich source of information on Chinese firms, the ASIF data also suffer from some serious problems, such as missing data on key variables, vague variable definitions and measurement errors (Nie et al., 2012). To address these issues, I follow the procedures outlined in Brandt et al. (2012) to systematically clean the dataset and recover as much information as possible. I additionally require each firm to report at least 2 consecutive years of information during the 1998-2007 time period to avoid estimation issues and reduce noise in the data from the high number of firms that only report one year of information. In total, there are 198,982 firms only reporting in one year, accounting for 28.9 per cent. The sample size of firms used to carry out the subsequent methodological varies depending on the research questions and strategy and information availability for certain variables.

Due to the measurement procedures of the China Statistical Bureau, the threshold barrier of approximately $600,000 will inevitably introduce a certain degree of bias towards higher firm performance rates. This bias is limited, however, as the sales threshold barrier is not strictly enforced. For instance, over the time period of my analysis, 19% of state-owned enterprises (SOEs) and 5% of privately-owned enterprises (POEs) reported sales below the five million RMB sales threshold (Brandt et al., 2012). This is good because it decreases the chances that firms stop self-reporting due to dropping below the sales threshold. While a certain degree of threshold bias remains, incorporating a size threshold can be advantageous as well, because it removes noise in the data due to under-reporting by small firm start-ups

[1] All relevant variables are deflated using a sophisticated price index developed by Brandt et al. (2012).

(Audretsch et al., 2000).

3.2 Variable Development

For the remainder of the chapter, I will operationalize the theoretical framework introduced in the previous chapter. In line with the literature, I develop appropriate proxies to measure firm performance, innovation, agglomeration, policy and institutional quality. The subsequent empirical sections will rely upon these variables to carry out the proposed investigation; although in certain cases, the inclusion and development of some variables varies slightly, in accordance to the theoretical demands and data availability. Table 3.1 provides important information on the variables used in the subsequent empirical chapters. The first two columns indicate the variable code used in the respective models and the corresponding name. Column 3 shows the unit of analysis for each variable. Column 4 indicates what chapters the variable is invoked in the modelling sections. The final column provides a definition of the variable and how it was calculated.

3.2.1 Measuring Firm Performance: Dependent Variables

3.2.1.1 Firm Survival

I create my survival variable based on the entry, exit and duration (in years) of a firm. The entry year of the firm is identified for the first year, t, that I observe the firm but not in any years prior to t. Likewise, the exit year of the firm is defined as the last year, t, that the firm reported information but not in the year $t + 1$, $t + 2$, ..., 2007. The duration of a firm is defined by counting the number of years the firm is in operation, excluding the start-up year. All firms that entered and exited the survey in the same year are removed from the sample.

Because I am using panel data, I observe new start-ups at different point in time during the observation period, 1998-2007. The resulting effect is that firms enter my survey in different years, which is characteristic of left-truncated data. In addition, not all firms exit

Table 3.1: Variable Information

Code	Name	Level	Chapters	Definition
Dur	Duration	Firm	4	The # of years a firm is observed
TFP	Total Factor Productivity	Firm	5,6	Developed using the Olley and Pakes (1996) method
InnovD	Innovation Dummy	Firm	4	Firm reports positive new product or process sales (1=Yes, 0=No)
Innov	Innovation Intensity	Firm	5,6	Ratio of new product and process sales to # of employees
RDint	R&D Intensity	Firm	6	Ratio of expenditures on R&D to # of employees
RDch	R&D Choice	Firm	6	Decision to pursue R&D (0=No, 1=Yes)
Wage	Average Employee Wages	Firm	5	Amount of wages divided by # of employees
AbsCap	Human Capital	Firm	6	The product of the proportion of # of professionals (2004) x the ratio of expenditures on professional training to total sales (2005-2007)
Age	Age	Firm	6	Measured in Years
Size	Size	Firm	4,5	# of employees
Mktshr	Market Share	Firm	6	Firm's share of industrial output within its own industrial sector (3-digit)
LbrProd	Labor Productivity	Firm	4	Gross output divided by # of employees
Exp	Export intensity	Firm	5,6	Exports divided by total output
Subs	Subsidies	Firm	4,5,6	Amount of state subsidies divided by total firm sales
Levg	Leverage	Firm	4,5,6	Ratio of firm's long-term debt to total assets
DistP	Distance	Firm	6	Distance to nearest port (Km)
SPZ	Special Industrial Zone	Firm	5	Located in Special Industrial Zone (1=Yes, 0=No)
SOE	State-Owned	Firm	4	Majority share holder is the State (1=Yes, 0=No)
POE	Privately-Owned	Firm	4	Majority share holder is a private individual (1=Yes, 0=No)
FOE	Foreign-Owned	Firm	4	Majority share holder is a foreign company (1=Yes, 0=No)
LQ	Location Quotient	City	5	Ratio of the local employment to regional employment divided by the ratio of national employment in industry i to total national employment
Den	Labor Density	City	5,6	Working population divided by city area (km^2)
EG3	Agglomeration Measure	Industry	4,6	EG Index based on Ellison and Glaeser (1997)
Diversity	Industrial Diversity	Industry	4	Standardized inverse of the Herfindahl Index
Glob	Globalization	City-Industry	4,6	Average amount of exports, weighted by total outputs
IndProt	State Industrial Protectionism	Industry	4,5,6	Average amount of Industrial subsidies,weighted by total sales of industry
RegProt	Regional Protectionism	City	4,5,6	Inverse of the Average amount of taxes, weighted by total sales for each city
InstQ	Institutional Quality	City	6	The product of the average proportion of union members in 2004, weighted by working population x the average spending on labor insurance (2001-2003) for each city

my sample by the end reporting year, 2007; therefore, my data is also subject to right censoring. I account for my data being left-truncated and right censored in the ensuing non-parametric and parametric analyses carried out in the subsequent sections.

An important issue to consider is how to properly interpret firm exit. When a firm exits my survey I am not able to strictly discern among the following three reasons of exit: bankruptcy, merger or acquisition, or falling below the sales threshold. Similarly, in regards to firm entry I can not determine whether the firm is a genuine startup or the result of a merger or acquisition. Even though I can not equate firm exit to firm closure, I am confident that firm exit does signify financial distress within the firm. I make this claim for two reasons. First, the panel data was carefully constructed relying on unique numerical firm IDs to track firms. Information on the firm and owner name, industry, address, etc. are all used to construct the unique id and link firms over time. When possible, firms received a new firm ID if they go through restructuring, merger or acquisition (Brandt et al., 2012), thereby reducing the risk that firms exit my survey due to merger or acquisition.

3.2.1.2 Total Factor Productivity

Total factor productivity (TFP) is the second measure used to measure firm performance. TFP assumes the contribution from technological progress or institutional change, and is the difference between output growth and the weighted average of the growth rate of input factors. To derive the firm's individual TFP measures, we begin with the standard Cobb-Douglas product function:

$$Y_{i\in(r,s)t} = \Phi_{it} L_{it}^{\alpha_s} K_{it}^{\beta_s} \tag{3.1}$$

Where Y is the output produced by firm i within region r and sector s, L and K represent the labor and capital inputs, and α and β represent the production coefficients, which are allowed to vary by sector.

After log transformation, the equation can be expressed as:

$$y_{it} = \alpha_s l_{it} + \beta_s k_{it} + \phi_{it} \tag{3.2}$$

and the firm-level log-TFP can be computed as the residual:

$$\phi_{it} = y_{it} - \alpha_s l_{it} - \beta_s K_{it} \tag{3.3}$$

We estimate Equation (2) using ordinary least squares (OLS), individual firm fixed effects (FE) and a semi-parametric approach following Olley and Pakes (1996). Following Yang and He (2013), we prefer the Olley and Pakes (1996) approach because it controls for input-output simultaneity[2].

3.2.2 Independent Variables

3.2.2.1 Measuring Innovation

I develop several measures of innovation based on innovation input and innovation output indicators. I first measure innovation input using a firm's investment in research and development (R&D). To measure innovation output, I create a binary variable of innovation based on whether a firm reports new innovation sales (Yes or No). A firm is defined as being an innovator if it reports positive innovation sales – defined as sales from new processes or products – for at least one year during its lifetime[3]. Conversely, a firm is defined as non-innovative if innovative sales are zero for all reported years.

Of course, no proxy for innovation is ideal and a considerable amount of work has been carried out on how to measure innovation. The binary variable is limited in the sense it does not measure intensity, however it is appropriate in some cases and represents the overall innovative orientation of the firm. Zaltman et al. (1973) describes innovation as a process that contains multiple stages. Prior to implementation of a new product or process, firms must first engage in the "initiation" stage, which requires innovative firms to develop a market orientation strategy that is responsive to new market information well in advance to reporting innovation sales (Kohli and Jaworski, 1990).

[2]See Yang and He (2013) who dedicate an entire section to the estimation techniques used to construct our firm-level TFP measures using the same dataset.

[3]See Cefis and Marsilli (2005) for a similar classification scheme

Nevertheless, to deal with the shortcomings of the binary proxy for innovation, I also create a variable based on new innovation sales intensity. Typically, previous research on the firm innovation-performance innovation research relies only on measures of innovation inputs. A critical issue with using innovation inputs as a proxy for innovation, however, is that it does not show whether a firm is successful in converting that input (e.g. R&D spending) into innovation. Another limitation with using R&D inputs, or even patents, which are another measure of innovation output, is that it does not show whether the firm is able to bring the new product to market. Therefore previous work that purports a positive relationship between innovation-based inputs and firm performance does not necessarily equate to a positive relationship between actual innovation output and performance.

Even with using new innovation sales as the measure of innovation output, it is not without limitations. One key limitation is the issue of endogeneity, higher innovative firms are likely to produce more and likewise, higher productive firms are more likely to innovate. To deal with this issue, chapter 6 introduces a structural model of innovation that partitions out the effects of the firms' innovation efforts in the earlier stages of innovation (i.e. R&D). The structural approach adopted in Chapter 6 is in line with the most recent advancements in the literature and offers one of the most sophisticated ways of measuring innovation's effect on firm performance.

3.2.2.2 Policy and Institution Variables

Taking the important role of the state into consideration, I incorporate five policy variables that guage the effects of direct, regional and state forms of protectionism and policy on firm performance. I develop two proxies for direct state-protectionism at the firm level: amount of subsidies received from the government and the amount of loans received by the banks. Subsidies are divided by the firm's total sales and loans are divided by total assets - referred to as the firm's leverage. Both direct subsidies and granting access to loans are key state-interventionist strategies to protect local firms and are expected to increase firms' survival chances. The special productivity zone (SPZ) variable is a dummy variable indicating whether a firm is located within a state-orchestrated special industrial district.

The two protectionist proxies (state, regional) allow us to control for potential heterogeneous effects of various state actors on firm performance in the mid- to long-term. State industrial protectionism is calculated as the average amount of state subsidies weighted by total sales for each industry. To account for local protectionism, I construct a proxy that gauges the degree of preferential tax breaks at the city-level. Preferential taxes are a main vehicle for provincial and local government authorities to attract new business, as well as protect firms within its jurisdiction. To develop the proxy, I take the inverse of the average amount of taxes weighted by total sales for each city[4].

The spatially uneven devolution of decision-making powers from the state to the provincial and local authorities has led to geographical variation in the development of local institutions (Wei, 2000). To capture the regional differences in institutions I develop a simple proxy for institutional quality. Calculated at the city-level, I calculate the city size-weighted average of firms' spending on labor insurance (2001-2003) multiplied the city size-weighted average of firms' proportion of union workers in the labor force in 2004.

My institutional proxy captures the aspects of institutional building that improves employment and social protections, which will likely be attractive to high-skilled workers engaged in innovative activities. Moreover, my proxy takes into account the lagged time effects that usually occur with institutional change. My choice of 4-year time lags is reasonable and is partially driven by data availability. No proxy for institutional quality is perfect, however. The main drawback of my proxy is that neither higher labor insurance expenditures, nor higher proportions of union workers in the labor force necessarily equates to stronger structural support for innovation, such as the protection of intellectual property laws or infrastructure that facilitate technology transfers.

[4]I use the inverse for clarity purposes in interpreting the results. A positive coefficient indicates a positive relationship between local protectionism and firm performance.

3.2.2.3 Measuring Agglomeration

To proxy for the spatial concentration of economic activity, I construct two proxies that attempt to capture the localization economies generated from the Marshall-Arrow-Romer (MAR) externalities: (1) location quotient (LQ) and (2) the EG index developed in Ellison and Glaeser (1997). The location quotient is the most commonly utilized base analysis method, while the EG index is noted as being one of the most robust measures of spatial concentration that takes into account structural changes. I calculate both the LQ and the EG indices using employment information at the 3-digit industry level.

The measure of location quotients is calculated as follows:

$$LQ = \frac{e_{ir}}{e_r} \Big/ \frac{\sum_r E_i}{\sum_r E} \tag{3.4}$$

where e_{ir} is the employment in industry i in city r, e_r is total employment in city r, E_i is the national employment in industry i and E is total national employment. A ratio of 2 or higher indicates that industry i is localized and plays an important role in the local economy.

The EG index can be written in the following form:

$$\gamma_i = \frac{G_i - (1 - \sum_r x_r^2) H_i}{(1 - \sum_r x_r^2)(1 - H_i)} \tag{3.5}$$

$G_i = \sum (x_r - x_s)^2$ represents the spatial Gini coefficient, where x_r is the share of total employment of all industries in region r and x_s is the share of employment for region r in industry i. H_i is the Herfindahl index and is a measure of market concentration and is expressed as $H_i = \sum_i P_i P_i$, where P_i is the proportion of output of the individual firm weighted by itself for industry i.

I also develop two variables that proxy for inter-industry spillovers. First, I use the inverse of the Herfindahl index to proxy for industrial diversity. For my second measure, I use labor density to capture the urbanization economies generated by knowledge spillovers that result from the diversity of local industries. In addition, labor density also is related to the size of the agglomeration, the significance of collective resources and the size of the local labor market (Antonietti and Cainelli, 2011). I define labor density as,

$$Density = \frac{N_r}{A_r} \tag{3.6}$$

where N_r is the average size of the working population in city r weighted by the size of each city, and A_r is the area of the city (km^2).

3.2.2.4 Firm-Learning Proxies

I develop a set of firm learning proxies that take into account the firm learning process internal to the firm, between the firm and its environment, and external to the firm. I develop two proxies for learning internal to the firm: learning by doing (LBD) and learning by exporting (LBE). LBD is obtained by multiplying firm experience (age) by the firm's labor productivity in the previous year. Learning by exporting is obtained by interacting firm experience with the firm's export intensity in the prior year.

To measure the learning interactions that take place between the firm and the environment, I interact the firm's absorptive capacity (based on R&D intensity) with my agglomeration proxies (introduced above). External to the firm, I take into account how local institutions mediate the effect of agglomeration proxies on firm performance. I develop a simple proxy for institutional quality based on average spending on labor insurance (2001-2003) multiplied by a constant of the proportion of union workers in the labor force in 2004 for each city. No proxy for institutional quality is perfect. The main drawback of my proxy is that neither higher labor insurance expenditures, nor higher proportions of union workers in the labor force necessarily equates to stronger structural support for innovation, such as the protection of intellectual property laws or infrastructure that facilitate technology transfers.

Despite its drawbacks, my institutional proxy does capture the aspects of institutional building that improves employment and social protections, which will likely be attractive to high-skilled workers engaged in innovative activities. Moreover, my proxy takes into account the lagged time effects that usually occur with institutional change. my choice of 4-year time lags seems reasonable and is partially driven by data availability.

3.2.2.5 Other variables

A set of additional firm and environmental characteristics are also included in the empirical chapters, when necessary. For instance, certain firm characteristics, such as firm size, export-orientation, age, absorptive capacity, market share, and distance to port, are included in certain settings. Taking into account local environmental conditions, I also proxy the local development level as the average labor productivity weighted by the size of the working population, and use export-intensity, weighted by gross output, to control for globalization. Both the development and globalization proxies are likely to differ substantially based on industry and location; therefore, both variables are calculated at the region-industry level.

CHAPTER 4

The Mediation of State-Intervention on the Innovation-Performance Relationship: A Survival Analysis of New Chinese Firms

4.1 Introduction

In this chapter, I identify a set of key variables that impact firm survival, providing a glimpse into the changing firm dynamics and environmental conditions currently underway in China. Although a substantial theoretical and empirical body of research exists linking innovation and other determinants to firm survival, relatively few analyses examine transitional economies with imperfect markets and a strong state-presence. As a result of their exclusion, the determinants of survival in transitioning economies are not well understood (Deshpande and Farley, 2000), because findings from advanced capitalist economies may not be applicable to transitioning economies like China. This is because results based on Western countries may be highly country-specific, due to varying institutional organization (Falck, 2007); and second, transitioning economies, by definition, undergo substantial changes in their political, economic and legal institutions, which present new opportunities and challenges to innovative activities for enterprises (Child and Tse, 2001). This chapter makes an important contribution to the field by examining the role of innovation and state protectionism on firm survival in a transitioning and dirigiste economy.

I focus the study on determining whether innovative firms are more or less likely to out-survive non-innovative firms. I am also interested in examining the role of state-intervention on firm survival and, in particular, assessing whether different forms of protectionism (direct, local and state) have heterogeneous mediating effects on the innovation-survival relationship. The relationship between a firm's innovative activity and its survival is not inherently evident (Sorensen and Stuart, 2000). The reason for this unclear relationship is because innovation is noted as being inherently risky and, in theory, can increase the likelihood of a firm's survival, as well as its financial distress and failure (Buddelmeyer et al., 2010). In the Chinese context, the uncertainty surrounding the returns to innovation is even more ambiguous given the heavy involvement of the state in the economy, which may supplant the important role usually attributed to innovation in Western, advanced capitalist economies.

To carry out these objectives, I use panel data on over 40,000 new start-up firms from 1998-2007 to examine the relationship among policy, innovation and firm performance. Both non-parametric and parametric analyses are used to explore the returns to innovation in the presence of direct, local and state protectionism on firm survival. I attempt to answer the following questions: (i) Do innovative firms out-survive non-innovative firms? (ii) How does state industrial policy and/or local protectionism mediate the relationship between innovation and firm survival? and (iii) Based on the statistical evidence, does state protectionism likely increase or diminish the risks associated with pursuing innovation?

The remainder of the paper is outlined as follows. In the next section, I describe the model specification. Sections 3 and 4 present the respective non-parametric and parametric results. Section 5 concludes with a summary of the results and final remarks.

4.2 Model Specification

Hazard analysis – including non-parametric, semi-parametric, and parametric approaches – is commonplace in the survival literature, and describes the conditional probability of survival for a business in a time span $t + \Delta t$. Unlike other approaches that study firm exit, such as probit/logit, duration analyses can account for censoring and truncation, and provides duration (Coleman et al., 2012).

Semi-parametric approaches to survival analysis – e.g. Cox's hazard model – are most often invoked for firm survival studies because the researcher need not make any assumptions about the underlying distribution. The main disadvantage of the semi-parametric approach (i.e. Cox regression), however, is that its proportionality assumption is unlikely to hold true when examining multiple cohorts (Falck, 2007; Agarwal and Audretsch, 2001) To check whether the proportionality assumption is indeed violated in my case, I re-run my models below estimating the semi-parametric Cox hazard model. I examine the scaled Shoenfeld residuals and obtain a value of 1330 (p-value = 0.00), with similar results obtained for the independent variables as well. Therefore, shifting the baseline hazard function by the same proportion at any time period is not appropriate in my case. For that reason, I opt for a parametric approach and estimate accelerated failure time models, which unlike the Cox regression, have a time-scaling factor that increases (decreases) the probability of failure when the value is greater (lesser) than 1.

The subsequent section begins with a non-parametric analysis. I use the Kaplan-Meier (KP) estimator – a simple frequency estimator – to calculate survival probabilities. The KP estimator is given by

$$\hat{S}(t) = \prod_{t_i <= t} (1 - \frac{d_i}{n_i}) \tag{4.1}$$

where n_t denotes the number of firms at risk at time t, and d_t is the number of exits at time t.

Following the non-parametric analysis, I specify several accelerate-failure time (AFT) models taking into account left truncation and right censoring. The likelihood function in general form is:

$$L = \prod_{i=1}^{N} \left[\left[\frac{f(T_i)}{S(E_i)} \right]^{c_i} \left[\frac{S(T_i)}{S(E_i)} \right]^{1-c_i} \right] = \prod_{i=1}^{N} \left[h(T_i)^{c_i} \left[\frac{S(T_i)}{S(E_i)} \right] \right] \tag{4.2}$$

where f(t) is the density function and S(t) is the survival function. E_i takes into account the left truncation, giving the first time a firm enters into the panel; c_i takes into account right censoring and takes the value of 1 for firms that fail and 0 for firms that are still active at the end of observation time. In log form, the log-likelihood function can be re-written as:

$$lnL = \sum_{i=1}^{N} \left[c_i \, ln \, h(T_i) + ln \left[\frac{S(T_i)}{S(E_i)} \right] \right] \tag{4.3}$$

In order to estimate the hazard function, I must first choose an appropriate underlying distribution. Following Falck (2007), I select the log-logistic distribution, which has a flexible form that allows for monotonous functional forms, and other shapes as well. The hazard function with a log-logistic distribution is:

$$h(t, X_i) = \frac{{\psi_i}^{1/\lambda} \, t^{(1/\lambda - 1)}}{\lambda \, [1 + (\psi_i \, t)^{1/\lambda}]} \tag{4.4}$$

where $\psi_i = exp(-X_i\beta)$ and is the time-scaling factor that decreases survivial time for values greater than one. The shape of the function is determined by λ. For $\lambda >= 1$, the functional form is decreasing monotonously and $0 < \lambda < 1$ has a bell-shaped form

The smoothed hazard function is presented in Figure 4.1. The form of the hazard function reaches its maximum at the time of start-up, and monotonously declines over time, thereby offering some initial support that the log-logistic regression is appropriate. In the models presented below, I obtain $\lambda >= 1$, indicating that the functional form is indeed monotonously declining over time[1]. Figure 4.1 also indicates that firms face the highest risk of exit during their initial start-up year. This finding is in stark contrast to findings from firm survival studies carried out in Western countries. For example, previous studies tend to find a bell-shaped hazard function (Bruderl et al., 1992; Wagner, 1994; Falck, 2007). The high hazard rate at time of start-up attests to the competitive climate in which new firms must operate; as more successful firms are able to adapt to the market conditions, their hazard rate decreases with experience.

4.3 Non-parametric Results: Survival Analysis

A semi-balanced panel is constructed resulting in 41,924 new enterprises that are in operation from 1998 to 2007. Table 4.1 provides the number of new start-ups and innovators by year, along with corresponding exit rates. Of the 41,924 firm start-ups, 5,714 (13.6%) report positive innovation sales at some point during the observation period. On average, 28% of firms will exit in any one year. Once disaggregated into innovators vs. non-innovators, less than 20% of innovative firms will exit in any one year, compared to 30% of non-innovative firms.

To investigate potential cohort-effects related to time of firm entry, I report survival probabilities for each entry cohort from 1998 to 2004 after 2-, 4- and 6-years subsequent to

[1] Although not reported in this paper, I re-run my hazard models using alternative distributions – Weibull, Exponential and Log-Normal – as an additional check for model accuracy. The AIC values computed using the log-likelihood are lowest for the log-logistic model, confirming that the log-logistic distribution is the best choice.

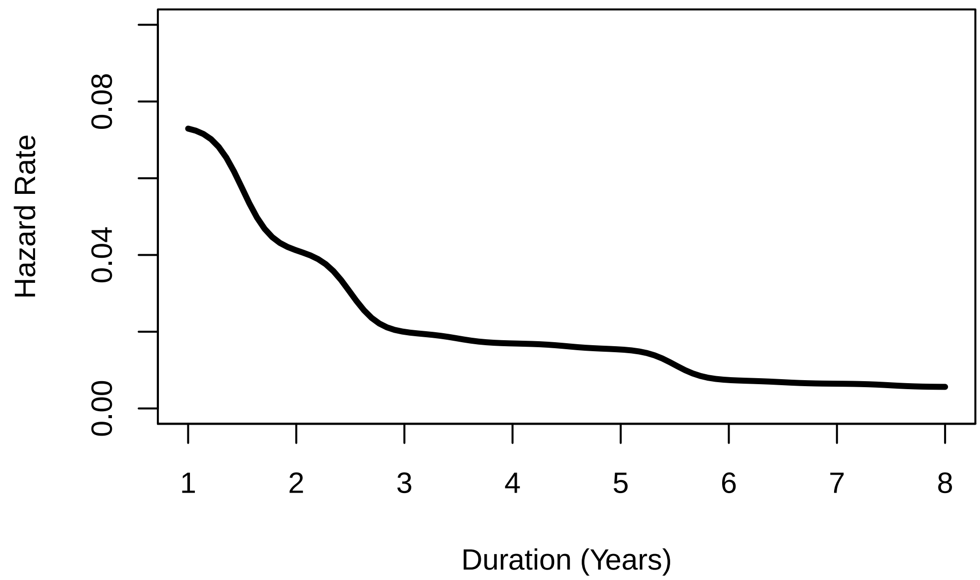

Figure 4.1: Smoothed Hazard Function, 1998-2007

Table 4.1: Annual Number of Start-ups by Innovators and Exit Rates, 1998-2007

	Start-ups	Exit %	Innovators	Exit %	Non-Innovators	Exit %
1998	3,701	...	766	...	2,935	...
1999	1,811	22.7	324	6.2	1,487	26.3
2000	1,871	47.8	350	21.4	1,521	53.8
2001	3,808	15.9	631	9.0	3,177	17.3
2002	2,649	35.1	397	20.4	2,252	37.7
2003	3,605	46.1	415	39.0	3,190	47.0
2004	9,313	9.7	1,325	6.1	7,988	10.3
2005	7,217	21.7	755	19.2	6,462	21.9
2006	7,949	24.9	751	28.6	7,198	24.6
Total	41,924	27.9(*Avg.*)	5,714	18.7(*Avg.*)	36,210	29.8(*Avg.*)

entry. According to Table 4.2, time-effects do appear to affect survival chances. On average, over 90% of innovative firms survived after two years, compared to only 77% of non-innovative firms. Over time, the role of innovation appears to play an even more important role for survival as the gap in survival chances between innovators and non-innovators widens after

4 and 6 years respectively. By the end of 6 years, less than half of non-innovative firms survive, compared to over 70% of innovative firms.

Looking at a specific cohort , an examination of the non-innovative firms part in 1998/1999 reveals noticeably lower survival chances relative to later cohorts. The 1998/1999 cohorts' low survival chances after 2-years of duration likely reflects the difficulties for non-innovative firms to survive during times of crisis, i.e. the Asian Financial Crisis. Moreover, their persistent low rates of survival – after 4- and 6-years of duration – notably reflect the inability of non-innovative firms to find a competitive edge in the rapidly changing market conditions following China's entry into the WTO in 2001. On the other hand, innovative firms from the same 1998/1999 entry cohorts maintain survival rates comparable to later cohorts, revealing early innovative firms' effectiveness to withstand times of crises, as well as adapt to market changes and increasing competition.

Table 4.2: Firm Survival (%) by Cohort and Innovation, after 2, 4 and 6 Years

	After 2 Years		**After 4 Years**		**After 6 Years**	
	Inactive*	Innovative	Inactive	Innovative	Inactive	Innovative
1998	69.6	90.3	53.2	82.9	40.0	72.5
1999	67.2	89.8	46.4	79.0	38.0	71.3
2000	82.2	89.4	60.2	78.3	51.0	69.7
2001	74.8	90.3	63.9	85.1	...	...
2002	78.6	93.5	69.4	87.2	...	...
2003	85.0	96.4	...	...	...	...
2004	83.4	90.9	...	...	...	...
Avg.	77.3	91.5	58.6	82.5	43.0	71.2
St. Dev.	6.4	2.3	8.1	3.4	5.7	1.1

* Inactive indicates that a firm does not report positive innovation sales

Figures 4.2 and 4.3 below reveal the geographical variation of average 3-year survival probabilities and concentration of innovative firms, respectively. Clear regional patterns emerge in both figures, providing not only justification for the regional approach adopted in my parametric analyses below, but also revealing sharp regional disparities in terms of survival rates and concentration of innovative activity.

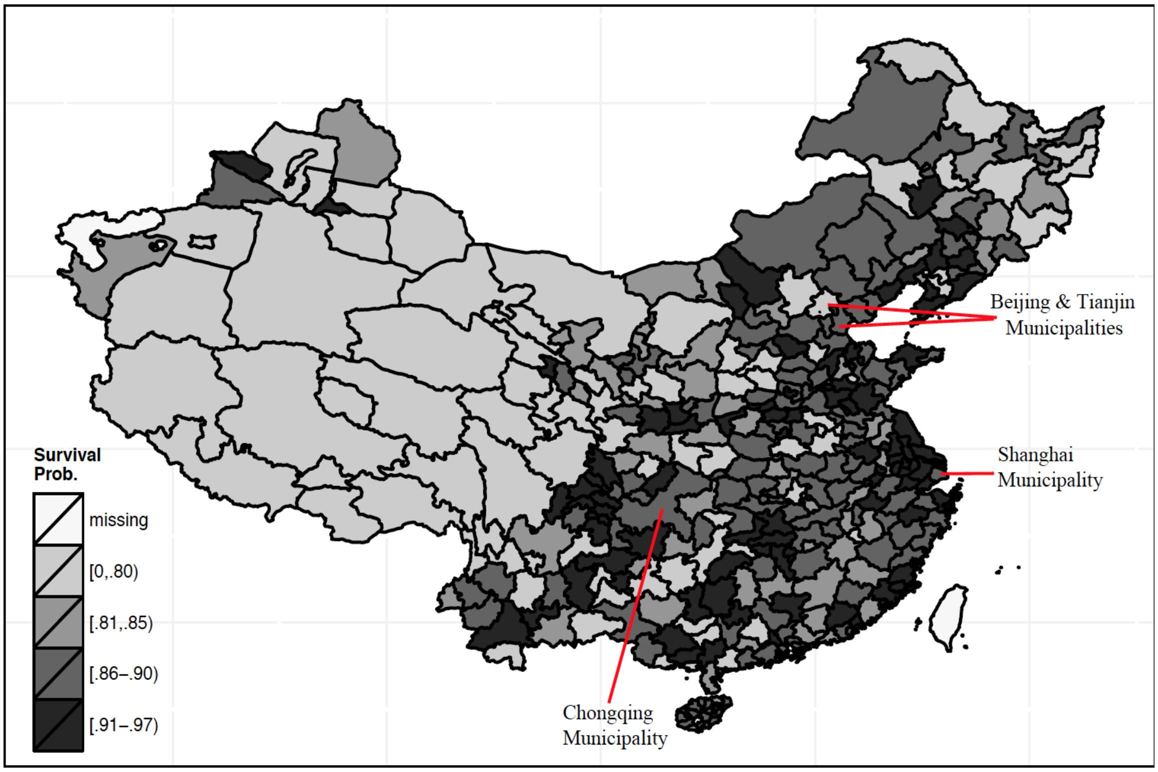

Figure 4.2: Average 3-year Survival Rates, 1998-2007

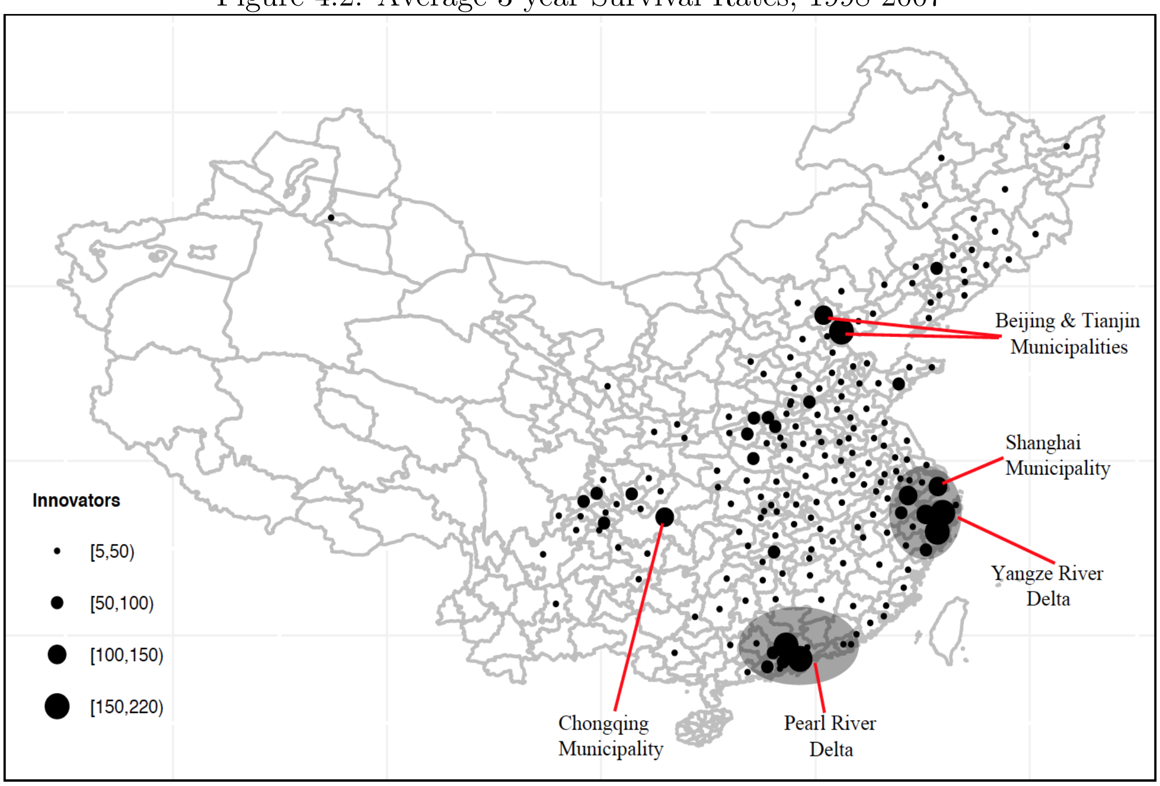

Figure 4.3: Number of Innovative Start-ups, 1998-2007

In Figure 4.2, clusters of high survival emerge around China's four municipalities (Beijing, Tianjin and Shanghai in the East, and Chongqing in the West). To a lesser extent there are also high survival clusters along the maritime (Guangdong and Fujian Provinces) and land borders (e.g. parts of Heilongjiang, Inner Mongolia, Yunan and Xinjiang). In general, however, firms that locate in western provinces suffer from (in some cases, substantially) lower chances of survival relative to cities located in the southwest, eastern coastal and northeastern regions.

The concentration of innovation clusters presented in Figure 4.3 correspond almost exactly to the high survival clusters in Figure 4.2, providing some initial evidence that firm innovation and performance are positively correlated. Not surprisingly, the largest innovation clusters are along the Yangtze River Delta and the Pearl River Delta, well known for their high-tech innovation centers. Smaller clusters farther north along the coast also exist in Beijing and Tianjin and inland in Henan province and Chongqing municipality.

Perhaps the most revealing piece of information from Figure 4.3 is the scarcity of innovative firms located in western cities. Of the almost 6,000 innovative firms captured in my sample, almost no western cities (except Chongqing) attracted more than 15 innovative firms to their jurisdiction. Despite various economic policies to develop the western provinces (e.g. Develop the West initiative, enacted in 1999), various policy incentives and increasing wages in the coastal provinces do not appear to outweigh the perceived advantages of co-locating in cities with other innovative firms. In the parametric analyses presented below, I delve deeper into the linkages between innovation and survival controlling for agglomeration forces and institutional policies.

From Figures 4.2 and 4.3 above, a clear relationship between innovation and survival is apparent. To further the examination between innovation and survival, I use the KP estimator to plot the grouped survival probabilities separately for innovative and non-innovative firms (Figure 4.4). The figure reveals that innovative firms have higher survival probabilities for each year of duration. The survival gap between innovative and non-innovative firms is most severe following the first year, highlighting the advantages that early innovation has on survival. After the first year, the gap between innovative and non-innovative consistently increases into the fifth year of duration, underscoring the sustained importance of innovation over time. Following the fifth year, the gap between innovative and non-innovative firms levels off, remaining fairly constant between the sixth and ninth years. For the 1998 cohort, approximately 75% of innovative firms survived the entire 9-year time span, compared to only 55% of non-innovative firms.

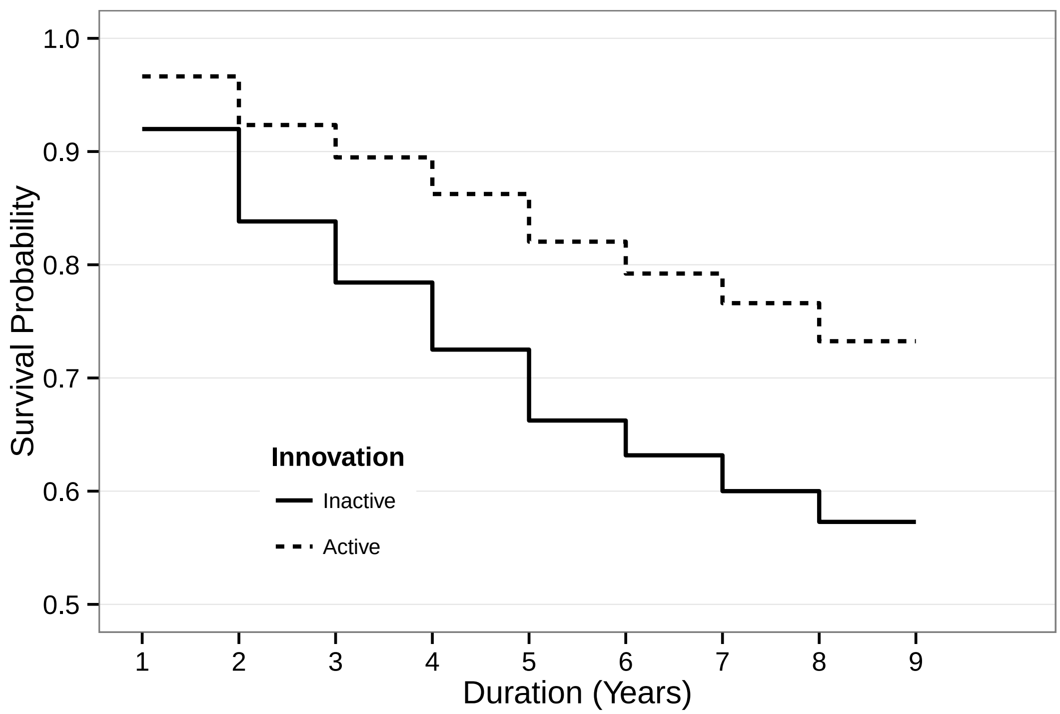

Figure 4.4: Survival Rates by Age for Innovative and non-Innovative Firms, 1998-2007

4.4 Model Empirics: Accelerated Failure Time Models

Table (4.3) presents the results for the firm-level log-logistic hazard regression. For ease of interpretation, results are reported as survival probabilities. A positive (negative) coefficient indicates a positive (negative) impact on firm survival. All models include industry fixed-effects. Variables are reported in 1-year lagged form to reduce issues of endogeneity. See Table 4.4 in the Appendix to see the summary statistics of variables. Model (1) includes innovation and size, controlling for ownership and region. Model (2) adds firm-level protectionist proxies. Model (3) adds additional environmental factors including geographic concentration of firms, state and local protectionism, economic development and globalization. Models (4) and (5) include interaction terms to detect whether protectionist policies produce heterogeneous outcomes depending on whether or not the firm is an innovator. All models return highly statistically significant χ^2, indicating the joint significance of the variables included in the model.

Table 4.3: Accelerated Failure Time Models

	Models				
	(1)	(2)	(3)	(4)	(5)
Innov	0.632***	0.630***	0.562***	1.164***	6.418***
Size	0.0003***	0.0003***	0.083***	0.091***	0.083***
Sub		0.091***	0.087***	0.078***	0.086***
Sub^2		−0.137*	−0.145***	−0.139***	−0.144***
Levrg		0.223***	0.251***	0.246***	0.301***
Levrg^2		−0.009***	−0.009***	−0.009***	−0.009***
StateProt			0.117***	0.117***	0.127***
RegProt			1.426***	1.426***	1.684***
EG3			0.514***	0.512***	0.517***
EG3^2			−0.633***	−0.630***	−0.626***
Diversity			0.089***	0.089***	0.089***
LbrProd			0.343***	0.344***	0.345***
Globz			0.353***	0.351***	0.352***
SOE	−0.491***	−0.502***	−0.401***	−0.399***	−0.396***
FOE	−0.027	−0.024	−0.003	−0.005	−0.002
NE	−0.104***	−0.105***	0.165***	0.163***	0.166***
Central	−0.159***	−0.162***	0.098***	0.096***	0.097***
West	−0.113***	−0.120***	0.187***	0.188***	0.193***
Innov*Size				−0.051***	
Innov*Sub				0.053*	
Innov*Levrg				0.051	
Innov*StateProt					−0.101***
Innov*RegProt					−2.603***
Constant	2.042***	1.713***	−5.308***	−5.357***	−5.859***
N	41,924	41,924	38,223	38,223	38,223
Log likelihood	−31,473	−31,459	−108,178	−108,158	−108,138
chi^2	1,131***	1,159***	8,926***	8,966***	9,005***

*p < .05; **p < .01; ***p < .001

In all five models, the statistically significant positive coefficient on innovators indicates that firms with successfully innovative strategies increase their survival probabilities. The size of the firm is also highly significant and positive, suggesting larger firms survive longer than smaller firms. Relative to privately-owned enterprises (POEs), the results indicate that state-owned enterprises (SOEs) have substantially lower survival rates[2]. Although local governments are most likely to protect SOEs relative to other types of enterprises (Lu and Tao, 2009), the finding is expected given the large-scale dismantling of SOEs since the early 1990s.

In Model (2) I include firm-level measures of state-protectionism and find significant, positive coefficients suggesting that firm subsidies and access to loans lead to favorable outcomes. Both measures, however, are subject to non-linear effects indicating that after a certain threshold, highly subsidized firms and over-leveraged (high debt-to-equity) firms are more likely to perform poorly. This finding provides some justification for the state to provide a certain degree of protectionism for new start-ups, although providing large amounts of subsidies or unfettered access to bank loans is likely to result in financial distress over time.

I include industry- and region- level factors in Model (3) to control for the operational environment of the firm, producing several interesting findings. Firms that operate in agglomerated industries and locate in diversified cities are respectively, associated with higher rates of survival. These result are not entirely anticipated. Firms in spatially concentrated industries can benefit from various forms of externalities – most notably knowledge spillovers; at the same time, spatial agglomeration also indicates greater rates of firm-entry and intensifying competition, which are more likely to lead to lower chances of survival. This notion is characterized by the market density hypothesis found in Audretsch and Mahmood (1995) and has received some support in the survival literature (Mata and Portugal, 1994; Falck, 2007).

To better determine whether there is a tipping point between positive externalities and the "competition effect", I include a non-linear term – $EG3^2$ – to account for negative externalities commonly observed with increasing agglomeration. I find a statistically significant, negative coefficient, indicating that after a certain agglomeration threshold is reached, the

[2]A firm is designated as being privately-owned if if the majority of its capital is privately owned; similarly, firms are defined as an SOE if the majority of equity is state-owned.

ensuing competition and congestion effects will eventually erode away the positive externalities associated with knowledge spillovers.

I also introduce two additional terms in Model (3) to control for institutional protectionism, distinguished between state protectionism and local protectionism. Similar to the firm-level results, I find that both types of institutional protectionism increase the rates of survival for firms that enter into protected industries and/or cities. The larger magnitude of local protectionism, however, suggests that local officials may experience better success at protecting firms within their jurisdiction relative to state-industrial policy.

In models (4) and (5), I introduce interaction terms between innovators and firm size, as well as with my multi-level institutional protection proxies. In model (4) I find a statistically significant negative relationship for the interaction with firm size and survival, meaning that large firms that undergo innovative activities face increased likelihood of experiencing financial distress. One reason to explain this outcome is that large innovative firms are likely to spend a large amount of resources on innovative-related activities, such as R&D; however, as an artifact of its size, it may be inefficient in the way it uses its resources to bring a new product or process to the market. This finding is supported in the allied literature on the impact of firm size on innovation, which posit that large firms are inefficient innovators relative to smaller firms (Scherer, 1965; Pavitt et al., 1987; Acs and Audretsch, 1991).

Upon examining the innovation-protectionism interaction terms I find that firm-level initial subsidies improve the performance of innovative firms (Model 4); however, in Model (5) I find the opposite effect. When I interact innovation with industrial subsidies (state protection) and regional tax preferences (local protectionism), both forms of protectionism decrease the survival chances of innovative firms. In other words, innovative firms that operate in industrial protected industries and/or cities have lower survival rates than non-innovative firms. This finding is likely explained by the fact that subsidies are directed towards propping up non-innovative, inefficient firms, who otherwise would exit earlier due to market conditions. However, state and local protectionism extend the lifetime of these inefficient firms, which leads to imperfect and non-competitive markets, and ultimately harms the operating environment for innovative firms.

4.5 Summary of Key Findings

I examine the innovation-firm performance (survival) relationship in the presence of economic distortions for new Chinese firms. My study reveals several important findings. First, firms engaged in innovative activities enjoy significantly higher rates of survival compared to non-innovative firms. Second, direct, local and state protectionism increase the chances of firm survival for all firms, although some of the effects are non-linear. In contrast, only direct subsidies increase chances of survival for innovative firms, whereas both local and state protectionism are found to harm the survival rates of innovative firms in the long-run. Lastly, the mediating effects of policy on survival varies according to the innovative strategy of the firm.

Additionally, several other findings presented in this paper are in-line with the outcomes obtained in advanced capitalist economies. For instance, I find that small, innovative firms are more likely to survive than large, innovative firms. One reason to explain this outcome is that large innovative firms are likely to spend a large amount of resources on innovative-related activities, such as R&D; however, as an artifact of its size, it may be inefficient in the way it uses its resources to bring a new product or process to the market. Conversely, large non-innovative firms assign their resources that generate greater returns to their investment. This finding is supported in the allied literature on the impact of firm size on innovation, which posit that large firms are inefficient innovators relative to smaller firms (Scherer, 1965; Pavitt et al., 1987; Acs and Audretsch, 1991).

Another key finding in my analysis indicates that the spatial scale of state-protectionism affects innovative firms in substantially different ways compared to non-innovative firms. While I do find clear evidence that suggests that short-run benefits exist for direct, local and state proxies of protectionism on firm survival, I find that too much direct intervention, i.e. highly subsidized and over-leveraged firms, leads to lower chances of firm survival. Moreover, in the long-run, I find that both local and state proxies of protectionism harm survival rates for innovative firms.

Based on the above findings, I conclude that the riskiness associated with pursuing innovative activities increases in the presence of prolonged state-protectionism, which tends to harms innovative firms in the long-run. One reason for this is because innovative firms must direct much time and resources to develop a successful innovation strategy, yet because they operate in a non-competitive environment they are prevented from accumulating the benefits, such as market dominance, normally derived from innovation in a competitive, market economy. These findings confirm the liberal-capitalist expectations that state protectionism prolong inefficient firms from exiting the market (Huang, 2003), thereby diminishing competition, which in turn, leads to unfavorable outcomes for innovation and firm performance (Fuller, 2008).

Some of the findings offered in this paper also point to progressive steps made by China as a result of its ongoing transition from a command economy to a market-led economy. Similar to the findings in Western, advanced capitalist countries, I find that both innovation and firm size directly increase a firm's survival chances. The positive coefficient on innovation was not only found to be robust to the inclusion of other variables, but it remained one of the most influential factors in determining the duration of a firm. Building a successful innovative strategy, therefore is of utmost importance for firms to remain competitive in the Chinese market, avoid spells of financial distress and extend duration periods. While this result is encouraging, my previous findings suggest that local and state protectionism may undermine some of the benefits that would normally be accrued to innovative firms in a more competitive, market-oriented economy. The policy relevance of this chapter suggests that maintaining a strong state-presence in the economy will pose difficulties for innovative firms, making it difficult for Chinese leaders to reconcile maintaining a strong state presence in the economy and achieving its recently emphasized goal of becoming a global innovative powerhouse by 2020.

4.6 Appendix

Table 4.4: Summary Statistics

	Mean	St. Dev.	Min	Max
Duration	4.156	2.435	1	9
Censor	0.180	0.384	0	1
Innov	0.136	0.372	0	1
Size	174.852	288.040	1	4,158
Sub	0.001	0.029	0.000	3.121
Levrg	0.060	0.272	0.000	21.000
StateProt	1.238	0.541	0.108	5.493
RegProt	9.076	0.378	5.398	10.836
EG3	0.015	0.015	-0.030	0.151
Diversity	5.540	1.158	0.000	8.127
LbrProd	4.060	0.645	0.000	10.160
Globz	0.154	0.177	0.000	0.802
SOE	0.057	0.232	0	1
POE	0.819	0.385	0	1
FOE	0.124	0.329	0	1
East	0.595	0.491	0	1
NE	0.083	0.275	0	1
Central	0.195	0.396	0	1
West	0.127	0.333	0	1

CHAPTER 5

Agglomeration and Firm Performance with Policy Distortions: Disentangling the Urban Premium from Firm Selection and Spatial Sorting

5.1 Introduction

The spatial concentration of economic activity has led to profound transformations in the global geo-economic landscape in recent history. Coinciding with the emergence of the 'new 'new' economic geography' (Ottaviano, 2011), the introduction of heterogeneous firm models has led to somewhat of a resurgence of research that promises to offer new insights into the effects of agglomeration on firm productivity (Baldwin and Okubo, 2006; Venables, 2011; Behrens and Duranton, 2010; Combes et al., 2012). Based on this line of research, the new agglomeration literature identifies spatial sorting and firm selection as two alternative explanations to urban increasing returns that may explain the empirically observed urban premium – firms produce more in agglomerative regions than firms located elsewhere.

While this new agglomeration literature treats the endogeneity issues that typically arise when trying to estimate the effects of agglomeration on firm production, they are specifically applied to advanced capitalist economies with mature markets, operating under the following assumptions: factors move freely across cities, no barriers to entry or exit, and limited government intervention. Such assumptions, however, are not valid when applied to the context of transitioning economies, especially China, where economic, and in particular, industrial policy remain largely responsible for steering the location, direction and intensity of the production of goods (Thomas, 2011).

This chapter estimates the effect of spatial agglomeration on firm productivity in three key Chinese industries – electronics, textiles and agro-food processing. Analyses are carried out on a panel of approximately 35,000 privately-owned enterprises operating in 333 different Chinese cities from 1998 to 2007. I carry out a set of non-parametric analyses, and subsequently, employ a penalized quantile regression with fixed effects to meet the following three objectives: (1) distinguish agglomeration effects from sorting and selection effects; (2) look at the impact of policy intervention variables (at the firm and spatial levels) across different quantiles of the firm performance distribution; and (3) examine the distortion effects of policy intervention on agglomeration variables and firm performance.

I carefully select the agro-food processing, textiles and electronics industries as case studies because together they provide a good representation of Chinese manufacturing in terms of concentration patterns, global integration, technological capability and extent of state-protectionism. For instance, the electronics industry is largely concentrated, globally integrated, technology-intensive and is a nationally strategic industry that receives a high degree of state subsidies. The textiles industry is also largely concentrated, globally integrated and heavily subsidized by the state, but is characterized as low technology-intensive. The agro-food processing industry is less concentrated, less integrated into the world market, medium technology-intensive, and receives far less state subsidies than the previous two industries. Based on their divergent industrial characteristics, I can contrast the effects of state involvement on firm performance and identify the agglomeration-sorting-selection relationship across the spectrum of industrial characteristics.

The structure of this chapter is as follows. Section 2 introduces the methodological approach. Section 3 presents descriptive statistics and a distributional analysis on firm TFP. Section 4 present the results from the FE models and FE quantile regression models and Section 5 concludes.

5.2 Model Estimation Strategy

Conventional panel models are overwhelmingly used to examine the agglomeration-firm performance linkages, albeit these types of models do not allow the researcher to discern the impacts of agglomeration from that of spatial sorting or selection. Conditional quantile regression is one alternative that can reveal the presence of sorting and selection.

The standard linear conditional quantile function, developed by Koenker et al. (1978), takes the following form:

$$Q(\tau|X = x) = x'\beta(\tau) \tag{5.1}$$

which is estimated by solving for the τth regression quantile,

$$\hat{\beta}(\tau) = \min_{\beta \in R^P} \sum_{i=1}^{n} \rho_\tau(\phi_{it} - x_i t' \beta) \tag{5.2}$$

for all quantiles $\tau \in (0,1)$. A key shortcoming with conditional quantile regression approach is that it fails to take into account account firm heterogeneity and as a result may produce biased estimates. For instance, Rigby and Brown (2013) find that agglomeration benefits tend to favor small, young firms. To take into account this problem, I extend the estimation procedure to include individual fixed effects that capture time-invariant firm characteristics. This technique is discussed by Koenker (2004) and implemented in various contexts by Matano and Naticchioni (2012).

The conditional quantile function with individual fixed effects is expressed as,

$$Q_{\phi_{it}}(\tau | x_{it}) = \alpha_i + x_{it}' \beta(\tau) \qquad t = 1, ...m_i, \quad i = 1, ..., n. \tag{5.3}$$

where ϕ_{it}, as defined in Chapter 3, is the log of the ith firm's TFP in year t. The α's are the unobservable time-invariant individual fixed effects and is a pure location shift effect on the conditional quantiles of the response. The covariates, x_{it} are assumed to depend on the quantile, τ, of interest, but the α's do not.

To estimate model (5) for several quantiles simultaneously, I perform the following estimation procedure,

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{t_i} \xi_k \rho_{\tau_k}(\phi_{it} - a_i - X_{it}\beta(\tau_k)) \tag{5.4}$$

where k is the index for the chosen quantiles (I use the 5^{th}, 10^{th},25^{th},50^{th},75^{th},90^{th},95^{th}). The piecemeal linear quantile loss function developed by Koenker et al. (1978) is denoted as $\rho_\tau(u) = u(\tau - I(u < 0))$. The weights, ξ_k control for the relative influence of the q quantiles on the estimation of α_i's parameters. Following Matano and Naticchioni (2012) I set the weights equal for all quantiles.

I assume the α's are constant across quantiles, which works to reduce the number of parameters to be estimated, and permits each chosen quantile, ρ_k to be estimated simultaneously. In the fixed-effect quantile regression a penalty term is added to the minimization algorithm to account for the computational problem arising from estimating a large number of individual fixed effects for the q quantiles. The penalty term involves shrinking the α's to a common value, which is useful when n is large relative to the m_i's, such as my case. This parameter penalization approach is beneficial because it significantly reduces the variability – introduced by the large number of α parameters that require estimating – of the estimate of the slope of β, all without sacrificing bias (Larmarche, 2010).

There are several penalty terms that can be selected. According to Tibshirani (1996), the ℓ_1 penalty term, $P(\alpha) = \sum_i = 1^n |\alpha_i|$, offers advantages over other penalty terms. Based on this recognition, I also select ℓ_1 to serve as the penalty term. The revised minimization algorithm that includes the ℓ_1 penalty term is expressed as follows:

$$\min_{\alpha,\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{m} \xi_k \rho_{\tau_k} \phi_{it} - a_i - X_{it}\beta(\tau_k)) + \lambda \sum_{i=1}^{n} |\alpha_i| \tag{5.5}$$

where the last term represents the ℓ_1 penalty term, and λ describes the importance of the penalty term in the minimization formula. As advised by Koenker (2004) and Matano and Naticchioni (2012), I set the penalty term to 1 for my estimations.

I estimate the following penalized fixed effects quantile regression for each industry:

$$\phi_{it} = \alpha_i + \beta_\tau X_{it} + \varphi_{1,\tau} PolicyFirm_{it} + \varphi_{2,\tau} PolicyCity_{it} + \gamma_\tau Agg_{it} + \lambda \sum_{i=1}^{n} |\alpha_\tau| \tag{5.6}$$

ϕ_{it} is the logged value of a firm's TFP at period t, X_i is a vector of firm characteristics, i.e. wages, size, exporter, innovator. $PolicyFirm$ is a set of firm-level protectionist policy proxies, $PolicyState$ is a set of local (city-level) or state (industry-level) protectionist policy measures. In total, I include six policy variables. Three variables – subsidies, tax preferences, and leverage – are firm-level variables that describe immediate effects of state intervention, while the other three – regional protection, state protection, and industrial district – are aggregate variables that account for the mid- to long-term effects of state protectionist policies. Taken together, the six different policy measures capture various channels of how the impacts of state-intervention can impact the economy over time. *Agg* is agglomeration variables that proxies for localization and urbanization economies. I discuss how each variable is derived in greater detail in the following section.

5.3 Non-Parametric Results: A distributional analysis on Firm Performance

In total, there are 12,299 agro-food firms, 17,868 textile firms and 4,828 electronics firms (Table 5.1). As mentioned earlier, the degree of state-intervention varies widely depending on the industry. On average, 37.7% of electronics firms received state subsidies, compared to 30.2% in textiles and 23.5% in agro-food[1].

Table 5.1: Number of Enterprises by Industry, 1998-2007

	Agro (N=12.299)		**Textiles (N=17868)**		**Electronics (N=4828)**	
Year	Firms	% Favored	Firms	% Favored	Firms	% Favored
1998	1107	27.5	1656	34.2	451	35.3
1999	1478	27.0	2136	34.5	631	35.0
2000	1878	25.3	3119	33.2	883	36.1
2001	2306	26.2	4602	32.5	1146	38.7
2002	2593	25.8	5754	32.3	1330	40.3
2003	3335	24.0	7372	31.0	1579	42.9
2004	3922	20.0	13015	27.2	2875	38.6
2005	5475	19.6	14377	25.6	3309	36.3
2006	6851	20.7	13975	25.7	3157	36.8
2007	5705	19.4	13068	25.6	2868	36.8
Mean	...	23.5	...	30.2	...	37.7

Figures 5.1-5.3 map the location quotients for the three respective industries under examination in 1998 and 2007. In 1998, the spatial pattern of firms in the agro-food industry is concentrated around the Bohai Sea in Shandong Province and neighboring Henan Province. By 2007, spatial clustering intensified around the Bohai sea, with new clusters emerging in northeast and some select cities in western China.

[1] If a firm received a state subsidy in any year of operation, I classify it as a "state-favored" firm, and as non-favored if no subsidies were received.

In Figure 5.2 shows that spatial clustering of firms in the textiles industry remain strongly concentrated around the Yangze River Delta (YRD) and the Bohai Sea. The magnitude of clustering is largely consistent from 1998 to 2007, indicating China's persistent reliance on textiles. One main change in the spatial pattern between the two years is the decline of industrial clustering in northeast China. In 1998, industrial clusters can be observed in 9 northeastern cities; in contrast, only two industrial clusters remain by 2007.

Figure 5.3 perhaps reveals the most interesting change in China's industrial location patterns. In 1998, only a handful of electronics industrial clusters existed (i.e. Beijing, Tianjin, Shenzhen), however, by 2007, several new industrial clusters emerged in the Pearl River Delta (PRD), near Shenzhen. In addition, several clusters popped up in various places along coastal China, most noticeably in the state-sponsored industrial districts of the YRD, connecting Shanghai with cities in neighboring Zhejiang and Jiangsu provinces.

Figure 5.4 presents the size-weighted average TFP by industry for 1998 to 2007. The textiles industry remained largely steady during the time period, with a slight increase during the 2004-2007 period. Both agro-food processing and electronics industries experienced greater perturbations, both ending with lower TFP levels at the end of the period than at the start.

Table 5.2 decomposes the TFP by favored status of the firm into deciles for each industry. On average, TFP in the agro-food sector is essentially equivalent between favored and non-favored firms. In the other two industries, favored firms return a 1.1% higher TFP in textiles and 2.6% in electronics. In electronics, the favored firms in the bottom levels of the distribution (deciles 1-3) return higher TFP relative to non-favored firms. Conversely, at the upper end of the distribution (decile 10), non-favored firms experience higher TFP levels relative to favored firms.

From these descriptive findings, state-protectionism is most effective in promoting technological upgrading for low-productivity favored firms, which produces a distinct advantage over their low- productive non-favored Chinese counterparts. On the other hand, at the upper end of the distribution state-protectionism may act as a prohibitive factor. For instance,

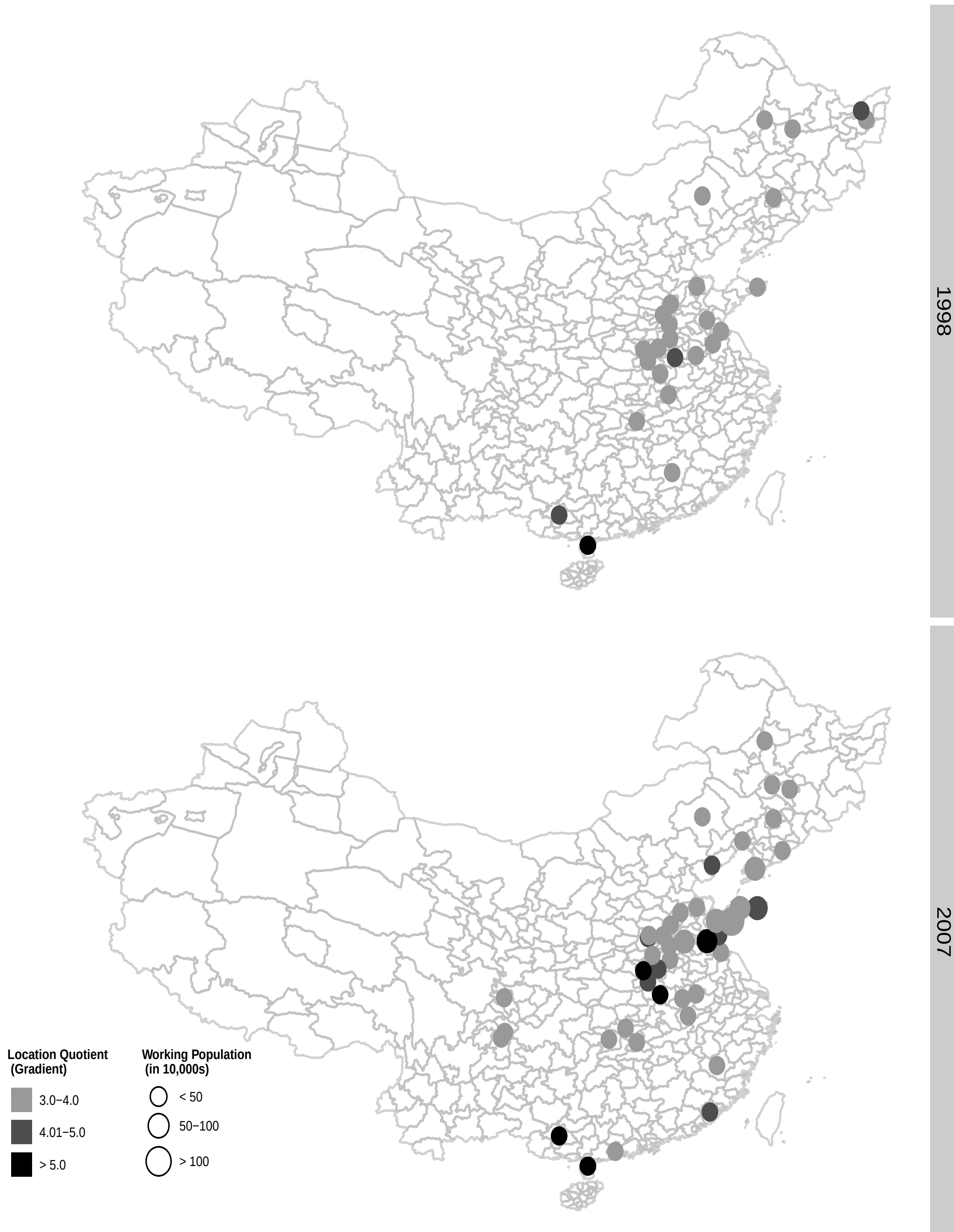

Figure 5.1: Agro-Food Processing-Location Quotient

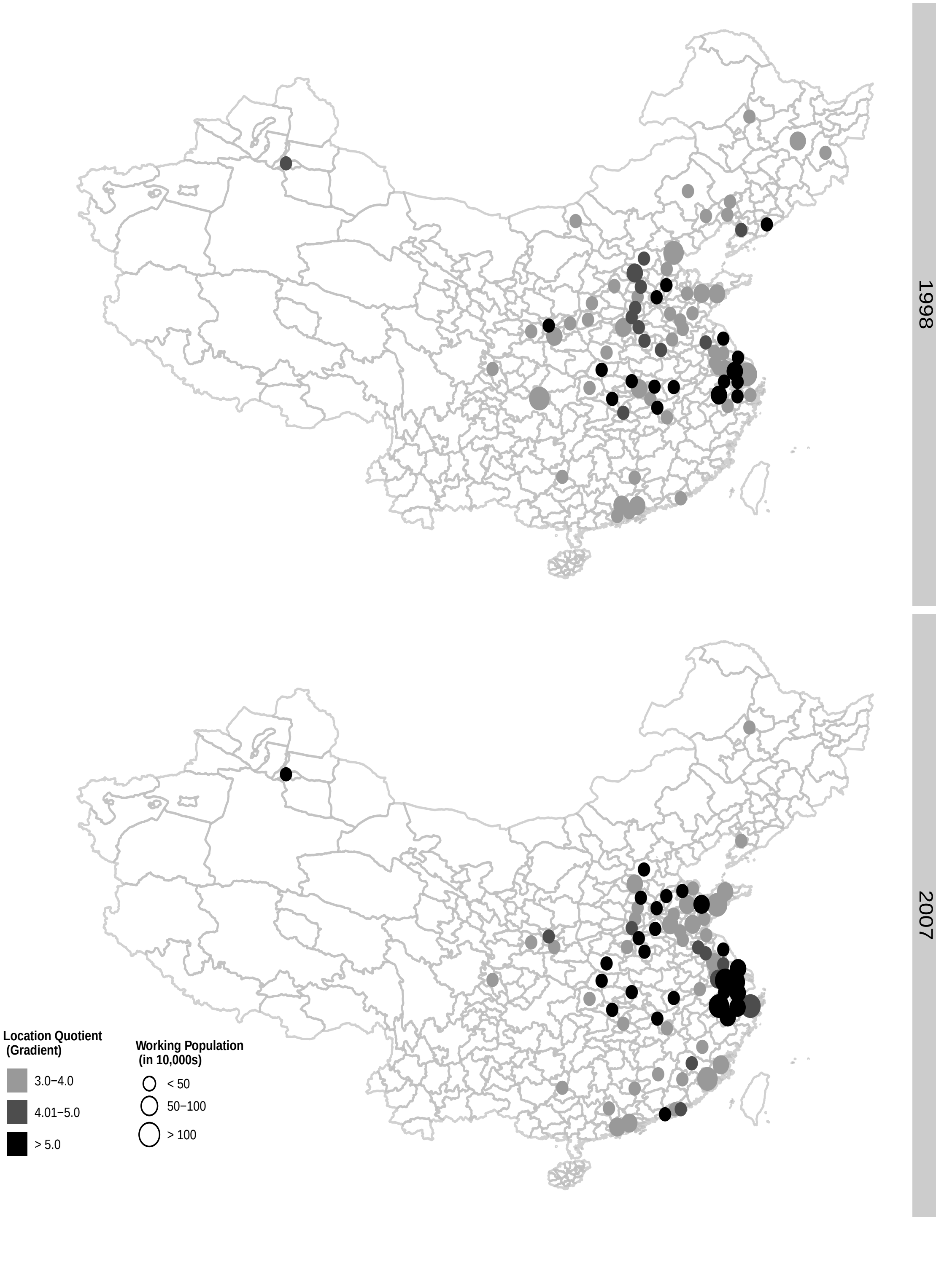

Figure 5.2: Textiles-Location Quotient

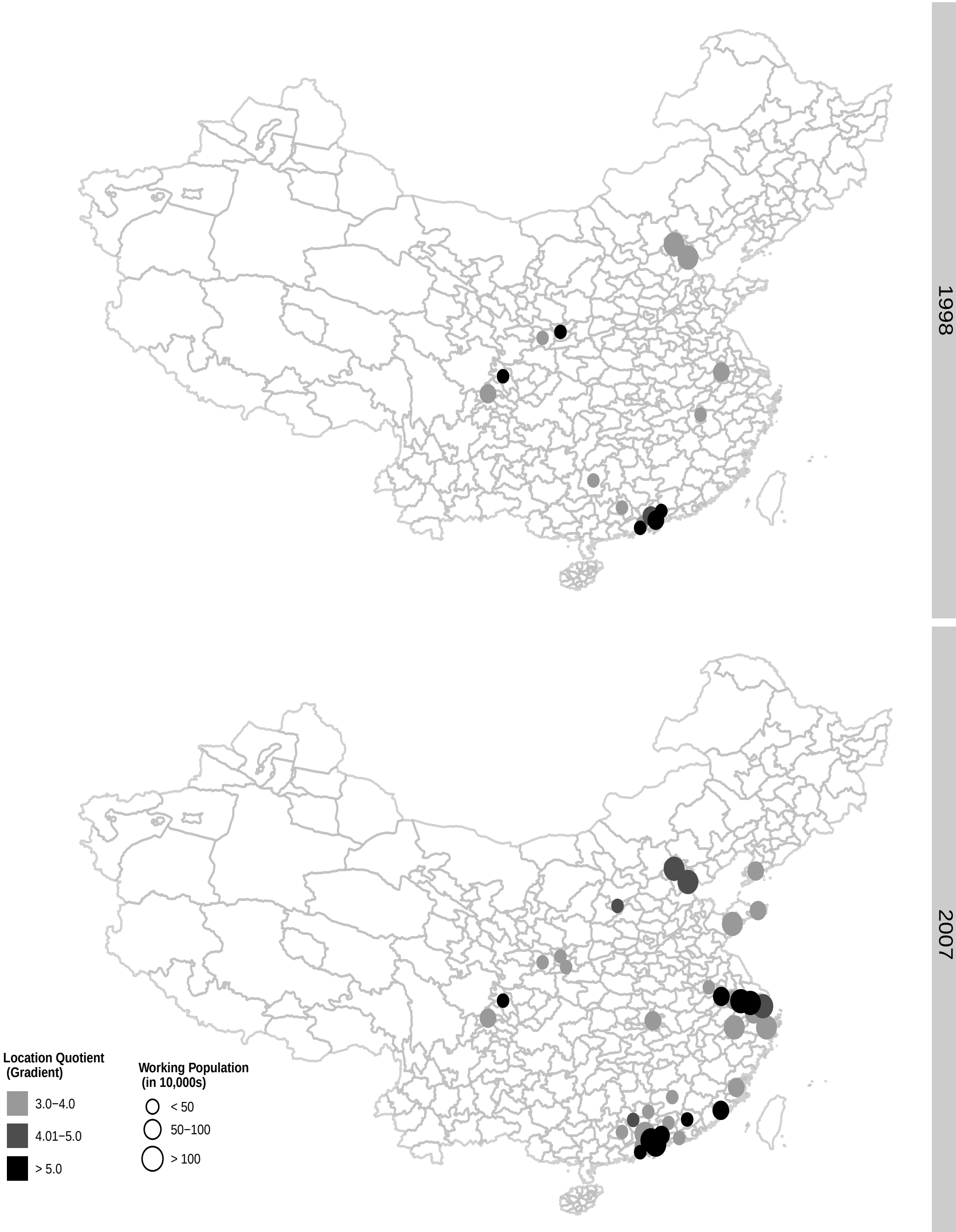

Figure 5.3: Electronics-Location Quotient

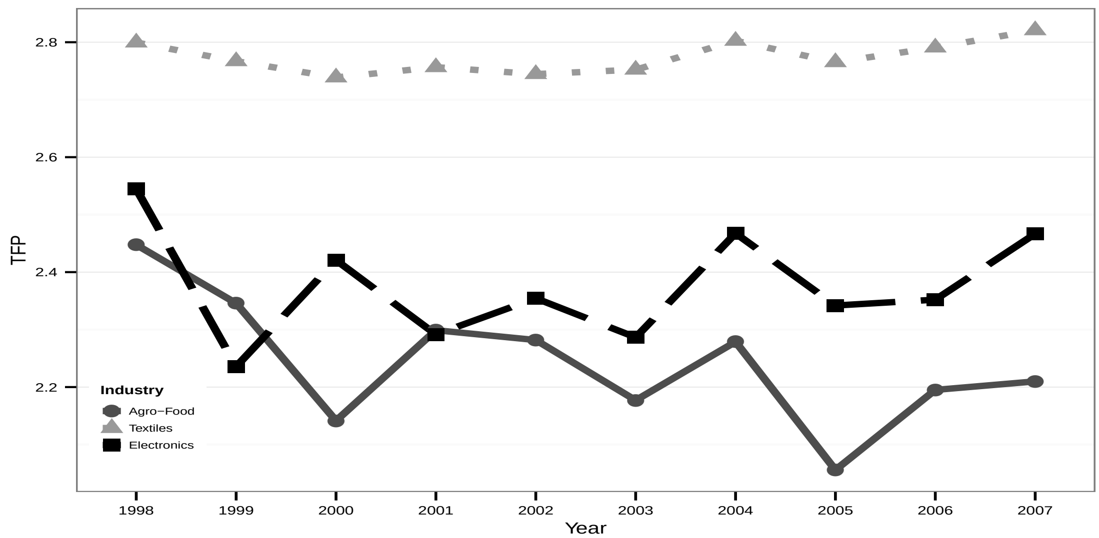

Figure 5.4: TFP by Industry and Year, 1998-2007

because high-productivity protected firms have unfettered access to state finance with littler to no state oversight (Huang, 2003), they are deprived of incentives to innovate and upgrade their technological systems. For the opposite reason, high-productivity non-favored firms that do not enjoy special protection from the government have greater incentives to upgrade technological systems to remain competitive.

Table 5.2: Favored Vs. Non-Favored Firms by Industry

	Agro		**Textiles**		**Electronics**	
	Non-FV	Favored	Non-FV	Favored	Non-FV	Favored
TFP	2.210	2.209	2.770	2.801	2.350	2.413
(in Deciles)						
1	0.507	0.442	0.735	0.703	0.768	0.796
2	1.718	1.737	1.749	1.765	1.730	1.750
3	2.096	2.097	2.105	2.111	2.091	2.098
4	2.352	2.350	2.356	2.350	2.353	2.347
5	2.572	2.567	2.577	2.589	2.576	2.575
6	2.795	2.805	2.795	2.798	2.788	2.794
7	3.021	3.015	3.019	3.027	3.010	3.012
8	3.282	3.288	3.285	3.285	3.283	3.282
9	3.646	3.630	3.643	3.634	3.655	3.642
10	4.495	4.459	4.303	4.243	4.524	4.458

Next, I estimate the kernel densities on the firm-level TFP for high- and low-concentrated regions according to industry and favored status of the firm. Figure 5.5 plots the kernel densities. The dashed line represents firms located in low concentrated cities with location quotient less than 1. The solid line represents firms located in high concentrated cities with location quotient of at least 1.

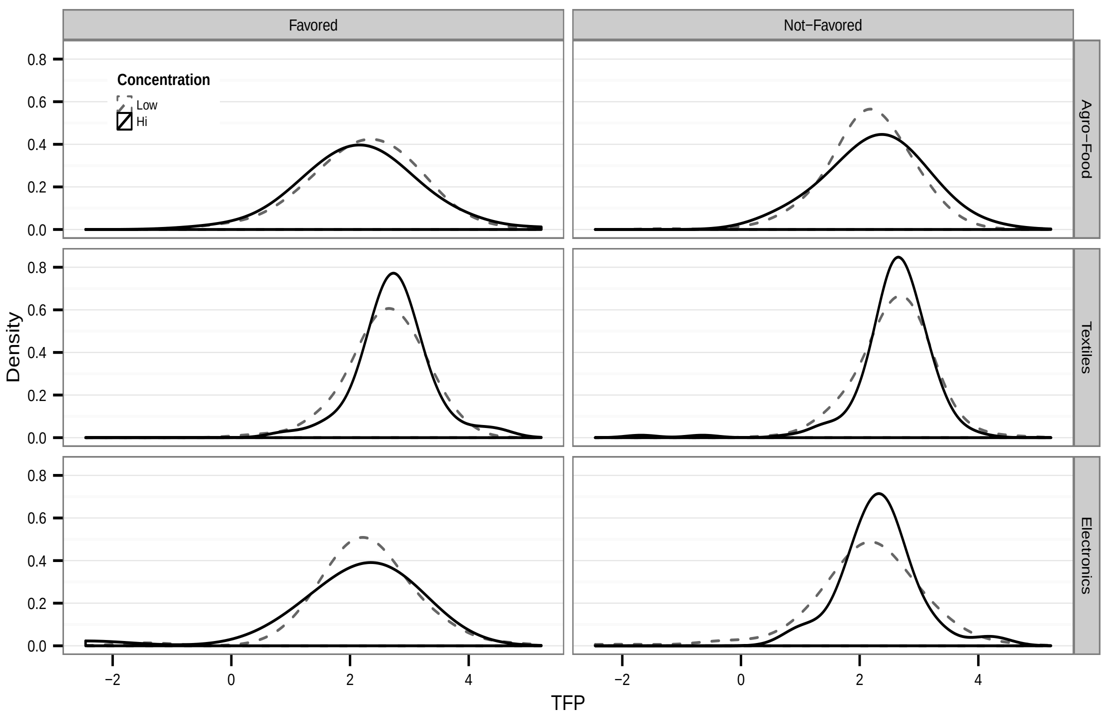

Figure 5.5: Kernel Densities on Firm-Level TFP by Favored Status and Industry

The presence of selection and sorting can be discerned by examining the effect of concentration at the tails of the TFP distribution. The selection process induces a left-truncation of the TFP distribution, therefore denser areas should exhibit higher productivity advantages in the lower tail of the TFP distribution (Combes et al., 2012). On the other hand, detecting spatial sorting is not as straightforward. Higher magnitudes concentrated in the upper tail of the TFP distribution is indicative of the sorting process or that agglomeration effects act heterogeneously according to firm performance. The latter explanation posits that some firms are better positioned to capture positive externalizes generated by agglomeration economies, which is supported in the literature (Rigby and Brown, 2013).

For the agro-food industry, the distribution of firms in high concentrated regions shifts left for favored firms, whereas it shifts right for non-favored firms. This indicates that favored firms are harmed by increasing industrial specialization, probably as a result of the competition effect. Non-favored firms clearly benefit from operating in higher concentrated regions, and the dilation effect (lower peak) indicates that the higher productive firms benefit more from being located in specialized regions.

In the textiles industry, the opposite relationship exists. The distribution of favored firms in high concentrated regions shifts right (slightly), while the distribution shifts left for non-favored firms. This puzzling result can be explained by observing that the truncation in the lower tail of the distribution for non-favored firms is stronger than for favored firms. The truncation effect reveals the presence of a selection effect for all firms, regardless of favored status. In this sense, state-protectionist policies have not effectively prevented low-productivity, inefficient firms from exiting the market.

One potential explanation for the right shift in the distribution for only favored firms may be explained by a sorting effect, where high productive favored firms are orchestrated by the state to enter high-concentrated markets to take advantage of perceived externalities, such as knowledge spillovers. This explanation is justified by looking at the upper tail of the distribution. In the absence of a dilation effect, the higher concentration of high-productivity firms observed for favored firms is characteristic of spatial sorting. Although as mentioned above, it could be that higher-performing firms are better able to benefit from positive externalities.

Several interesting results emerge from the electronics industry. Both favored and non-favored firms benefit from higher concentration in the electronics industry. One distinction, however, is that a left-truncation is observed for non-favored firms, but not for favored firms. In other words, the bivariate relationship reveals that protectionist policy mitigates the selection effect for favored firms. The strong dilation effect that I observe for favored firms indicates that the higher productive firms benefit more from intra-industry knowledge spillovers. This makes sense considering that low productive firms are likely to benefit less from such knowledge spillovers due to their own internal inefficiencies. Despite their inefficiencies, they are prevented from exiting the market due to their favored status.

5.4 Model Empirics: Fixed-Effects Panel Regression

At this point, I turn to a parametric approach to further investigate the existence of policy distortions, spatial sorting and selection. Because the focus of my analysis is on the policy and agglomeration variables, and their interaction with one another, it is important to briefly discuss the potential endogeneity concerns at this point. If policy intervention is endogenous, and, for instance, I find a negative coefficient on a policy intervention variable, then it would not be possible to discern whether government intervention is detrimental to firm competitiveness and TFP or rather than the government targets low productive firms for preferential treatment. This scenario is particularly relevant for the state-owned enterprise (SOE) sector, where it is well-known that the state funnels large amounts of subsidies and preferential tax breaks to under-performing and inefficient state-run companies (Huang, 2003).

In contrast, the sample of firms under this study is restricted to include only private entrepreneurial firms, in part, to reduce such endogeneity between policy interventions and firm performance. In the Chinese economy, it is not expected that low-performing private firms' receive a disproportionate amount of state subsidies, rather subsidies in the private sphere are more likely to be given depending on unobservable factors such as the entrepreneurs' connections to the state. Such unobservables are likely to be captured in the individual fixed effects and endogeneity bias is not likely to be a critical problem.

To deal with potential sources of endogeneity between agglomeration and firm performance, I develop an instrument using city's distance to port, as well as industry and year dummies[2]. The remaining explanatory variables are assumed to be exogenous, which is a

[2]The identification and use of proper instruments are noted as being notoriously difficult to find in the econometric literature. Geographical distance variables have been widely used as instruments for some time, especially in the growth literature. Although the development of my distance instrument is based on historical precedence, I also check to see whether the correlation between the excluded instruments and the endogenous explanatory variables is strong enough to permit instrument identification. Indeed, after obtaining the first-stage Walds F-test statistic, I reject the weak instrument hypothesis.

difficult assumption to make[3]. When possible, all variables are lagged by one year to possibly reduce endogeneity concerns.

The FE quantile regression model results are presented in Tables 5.3-5.5 below, corresponding to each of the three industries[4]. Individual fixed-effects are included in all models. Checking the model diagnostics, the pseudo-R^2 monotonically increases along the TFP distributions for each industry[5], indicating that my models aptly explain the performance of higher-productivity firms over time.

In all three models, I find wages to have a statistically significant positive impact on firm performance over time, albeit a generally decreasing trend is observed, which indicates that the higher-performing firms employ cost-saving strategies that reduce labor costs more effectively than low-performing firms. In regards to firm size, I find coefficients in the lower quantiles to be statistically significant and positive, although the coefficients turn negative at the higher ends of the TFP distribution; this relationship is similar across the three sectors. This finding indicates that larger firms over time tend to be low-performing, whereas smaller firms tend to be more efficient over time.

Exporting firms in the agro-food processing industry return negative coefficients across the TFP distribution (Table 5.3); conversely, innovative firms return positive coefficients for each quantile. Given that the agro-food processing industry is the least integrated into the global economy of the three sectors of analysis, it is not unexpected that firms in this sector are not globally competitive and have yet been unable to benefit from exporting. The positive findings on innovation offer some hope for strengthening the global competitiveness in this sector over time.

The coefficients on Sub and TaxBr are negative across the TFP distribution, although

[3]Firm-level characteristics, such as wage and size, are also likely to suffer from endogeneity. Various restricted models were estimated to test for sensitivity of the results to the adding or removing of endogenous terms. Findings remain consistent and robust regardless of the exclusionary restrictions. Therefore, any remaining endogeneity issues should be minimal. For brevity and clarity, only results from the unrestricted models are presented.

[4]See Tables 6 and 7 in the Appendix to see the respective summary statistics and variable correlations based on Pearson's coefficient.

[5]The pseudo-R^2 for each model is developed as in Koenker and Machado (1999), which is a local measure of goodness of fit based on the relative success of the corresponding quantile regression models at a specific quantile in terms of the weighted sum of absolute residuals.

Table 5.3: FE Quantile Regression: Agro-Food Processing Industry (N=19,476)

	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Wage	0.093 (0.018)	**0.119** (0.011)	**0.095** (0.008)	**0.085** (0.006)	**0.065** (0.007)	**0.029** (0.009)	0.009 (0.012)
Size	0.042 (0.033)	**0.046** (0.019)	**−0.037** (0.012)	**−0.053** (0.010)	**−0.076** (0.010)	**−0.106** (0.014)	**−0.108** (0.018)
Exp	−0.036 (0.074)	**−0.110** (0.048)	**−0.069** (0.031)	**−0.043** (0.025)	**−0.047** (0.028)	**−0.068** (0.036)	**−0.097** (0.044)
Innov	0.239 (0.089)	**0.132** (0.064)	**0.198** (0.052)	**0.160** (0.033)	**0.163** (0.040)	**0.341** (0.067)	**0.415** (0.074)
Sub	−0.101 (0.265)	0.010 (0.143)	0.009 (0.108)	−0.007 (0.089)	−0.034 (0.077)	−0.077 (0.087)	0.089 (0.201)
TaxBr	−0.746 (0.047)	**−0.681** (0.027)	**−0.660** (0.018)	**−0.658** (0.015)	**−0.653** (0.016)	**−0.618** (0.022)	**−0.613** (0.028)
Levrg	−0.002 (0.009)	0.001 (0.005)	−0.001 (0.003)	0.002 (0.002)	**0.007** (0.003)	0.005 (0.004)	0.003 (0.005)
RegProt	1.478 (0.813)	**1.872** (0.529)	**1.482** (0.354)	**1.790** (0.276)	**1.975** (0.291)	**1.465** (0.407)	0.693 (0.510)
StateProt	−0.041 (0.018)	**−0.045** (0.011)	**−0.025** (0.007)	**−0.028** (0.006)	**−0.027** (0.006)	**−0.037** (0.008)	**−0.045** (0.010)
SPZ	0.147 (0.148)	0.126 (0.094)	0.080 (0.081)	**0.126** (0.039)	**0.089** (0.048)	0.113 (0.070)	0.104 (0.075)
Den	−0.030 (0.027)	0.000 (0.017)	−0.016 (0.011)	**−0.035** (0.009)	**−0.036** (0.009)	**−0.043** (0.012)	**−0.026** (0.013)
LQ	0.010 (0.099)	0.059 (0.055)	−0.020 (0.034)	**−0.045** (0.025)	−0.012 (0.032)	0.034 (0.044)	**0.112** (0.053)
SubLoc	−0.351 (0.173)	**−0.205** (0.077)	**−0.088** (0.052)	−0.075 (0.050)	−0.048 (0.050)	−0.057 (0.060)	−0.010 (0.107)
Pseudo-R^2	0.06	.10	.11	.11	.17	.14	.20

Notes: Fixed effects are set to be constant across quantiles. The Penalty term is set to 1. For legibility considerations, bold coefficients indicate a statistical significance at the .05 level. The standard errors are obtained after 1000 panel bootstrap repetitions.

only the TaxBr coefficients are statistically significant. The monotonically decreasing coefficients on TaxBr indicate that low-productivity firms are disproportionately harmed by regional protectionism over time. Interestingly, firms benefit from regional protectionism regardless of their place along the performance distribution; on the other hand, firms located in cities with a strong central state presence reduce firm performance over time. This finding provides some initial evidence that the agro-food industry would benefit from greater decentralization measures that transfers decision-making powers from the center to the local city where local officials are more effective in implementing local policies.

Firm performance of firms located in denser areas tends to decline over time, symptomatic of a strong negative competition effect. Interestingly, only the high performing firms are able to benefit from localization economies, although it is not clear from the results whether this is because higher productivity firms are able to capture positive externalities or due to the sorting of high-performing firms into concentrated areas. The policy-agglomeration interaction term (Sub*LQ) returns negative values at each quantile of analysis, although the coefficients are only significant at the lower ends of the distribution. An indication that over time state subsidies disproportionately harm low-performing firms located in agglomerative regions. This finding is in line with economic theory in that a high degree of state subsidies lead to inefficient and non-competitive markets, thereby robbing firms of the incentives to upgrade production capabilities.

In the textiles industry (Table 5.4), exporting firms benefit from exporting over time across the TFP distribution, however, only the highest-performing firms are able to capture positive returns to innovation. In regards to policy, I find that over time direct subsidies, tax preference breaks and state protectionism result in negative effects across the TFP distribution. Regional protectionism, on the other hand, generates negative coefficients at lower ends of the distribution, but turns positive and increases along the higher ends of the distribution. This form of local protectionism clearly benefits high-productivity firms over time, but harms low-productivity firms.

Firms benefit from both localization and urbanization economies. For both the urbanization economies (labor density) and location economies (LQ), increasing magnitudes on the coefficients move from the lower to upper tails of the TFP distribution. There are two possible explanations for why I observe the monotonically increasing trend of coefficients on the agglomeration variables. First, high-productivity firms are sorting to higher concentrated areas to benefit from perceived positive externalities, such as knowledge spillovers. A second explanation is that higher-performing firms are in a better position to capture those externalities, which would support other findings that the effects of agglomeration are heterogenous according to firm characteristics (Rigby and Brown, 2013).

Table 5.4: FE Quantile Regression: Textiles Industry (N=56,046)

	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Wage	0.235 (0.008)	**0.204** (0.006)	**0.162** (0.004)	**0.128** (0.004)	**0.103** (0.004)	**0.085** (0.005)	**0.079** (0.008)
Size	0.112 (0.008)	**0.120** (0.006)	**0.108** (0.004)	**0.086** (0.004)	**0.047** (0.004)	−0.007 (0.006)	**−0.033** (0.008)
Exp	0.097 (0.016)	**0.095** (0.012)	**0.097** (0.008)	**0.099** (0.007)	**0.101** (0.008)	**0.080** (0.011)	**0.048** (0.016)
Innov	0.002 (0.022)	−0.014 (0.018)	**−0.028** (0.015)	**−0.022** (0.013)	−0.018 (0.014)	**0.048** (0.025)	**0.078** (0.031)
Sub	−0.060 (0.067)	**−0.114** (0.042)	**−0.089** (0.030)	**−0.103** (0.024)	**−0.115** (0.033)	**−0.101** (0.042)	**−0.167** (0.071)
TaxBr	−0.414 (0.013)	**−0.430** (0.009)	**−0.481** (0.006)	**−0.534** (0.006)	**−0.569** (0.007)	**−0.549** (0.009)	**−0.523** (0.013)
Levrg	0.007 (0.002)	**0.007** (0.001)	**0.007** (0.001)	**0.006** (0.001)	**0.007** (0.001)	**0.007** (0.001)	**0.009** (0.002)
RegProt	−1.582 (0.266)	**−1.192** (0.191)	**−0.469** (0.125)	0.169 (0.104)	**1.107** (0.134)	**2.239** (0.178)	**2.984** (0.265)
StateProt	0.005 (0.005)	**−0.009** (0.004)	**−0.032** (0.002)	**−0.044** (0.002)	**−0.055** (0.002)	**−0.066** (0.003)	**−0.068** (0.005)
SPZ	−0.006 (0.037)	−0.015 (0.027)	−0.020 (0.022)	−0.015 (0.018)	−0.002 (0.021)	−0.007 (0.024)	0.019 (0.047)
Den	0.035 (0.008)	**0.023** (0.006)	**0.019** (0.004)	**0.024** (0.004)	**0.038** (0.004)	**0.064** (0.005)	**0.069** (0.008)
LQ	0.056 (0.027)	**0.059** (0.019)	**0.067** (0.013)	**0.082** (0.011)	**0.087** (0.014)	**0.096** (0.019)	**0.099** (0.028)
SubLoc	−0.054 (0.026)	**−0.078** (0.021)	**−0.091** (0.014)	**−0.097** (0.013)	**−0.068** (0.015)	**−0.078** (0.021)	**−0.077** (0.028)
Psuedo-R^2	0.07	.11	.08	.14	.17	.15	.21

Notes: Fixed effects are set to be constant across quantiles. The Penalty term is set to 1. For legibility considerations, bold coefficients indicate a statistical significance at the .05 level. The standard errors are obtained after 1000 panel bootstrap repetitions.

The policy interaction term persistently returns statistically negative coefficients, indicating similar dynamics as in the agro-food processing: state-favored firms are unable to compete in agglomerative regions. Unlike the agro-food processing, the lowest quantile returns the smallest negative effect, meaning that low-performing firms are not as negatively effected as favored firms at other places in the distribution. This presents some indication that state-protectionist policies may be effectively promoting under-performing firms to become increasingly competitive in the textiles industry, although the persistent negative coefficient indicates that the competitiveness has not yet reached the level of non-favored entrepreneurial firms.

Table 5.5: FE Quantile Regression: Electronics Industry (N=12,016)

	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Wage	0.189	**0.187**	**0.177**	**0.157**	**0.132**	**0.102**	**0.072**
	(0.017)	(0.009)	(0.007)	(0.007)	(0.009)	(0.014)	(0.017)
Size	0.056	**0.061**	**0.039**	**−0.015**	**−0.064**	**−0.103**	**−0.127**
	(0.018)	(0.010)	(0.009)	(0.009)	(0.010)	(0.016)	(0.021)
Exp	0.124	**0.067**	**0.045**	−0.009	**−0.059**	**−0.151**	**−0.186**
	(0.034)	(0.022)	(0.017)	(0.017)	(0.019)	(0.031)	(0.040)
Innov	0.002	0.028	**0.074**	**0.128**	**0.210**	**0.273**	**0.325**
	(0.050)	(0.025)	(0.019)	(0.020)	(0.023)	(0.038)	(0.043)
Sub	0.181	**0.131**	**0.214**	**0.236**	**0.277**	**0.224**	0.169
	(0.087)	(0.051)	(0.052)	(0.044)	(0.056)	(0.098)	(0.120)
TaxBr	−0.546	**−0.546**	**−0.511**	**−0.530**	**−0.583**	**−0.596**	**−0.613**
	(0.026)	(0.015)	(0.012)	(0.012)	(0.014)	(0.022)	(0.029)
Levrg	0.014	**0.012**	**0.010**	**0.012**	**0.014**	**0.018**	**0.021**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
RegProt	0.923	**0.914**	**1.951**	**3.486**	**4.925**	**5.994**	**6.753**
	(0.544)	(0.326)	(0.221)	(0.226)	(0.254)	(0.411)	(0.510)
StateProt	0.004	0.003	**−0.011**	**−0.016**	**−0.024**	**−0.023**	**−0.029**
	(0.010)	(0.005)	(0.005)	(0.004)	(0.005)	(0.009)	(0.012)
SPZ	0.015	−0.013	−0.044	−0.063	0.007	0.037	0.067
	(0.091)	(0.053)	(0.047)	(0.046)	(0.063)	(0.099)	(0.164)
Den	0.054	**0.034**	0.006	−0.011	**−0.029**	−0.023	−0.009
	(0.019)	(0.012)	(0.009)	(0.009)	(0.011)	(0.017)	(0.022)
LQ	0.084	**0.095**	**0.080**	**0.048**	0.004	**−0.057**	**−0.137**
	(0.050)	(0.033)	(0.022)	(0.022)	(0.025)	(0.033)	(0.051)
SubLoc	0.038	0.007	0.011	0.024	0.021	0.035	**0.091**
	(0.045)	(0.029)	(0.021)	(0.021)	(0.023)	(0.036)	(0.050)
Psuedo-R^2	0.09	.11	.09	.16	.14	.17	.22

Notes: Fixed effects are set to be constant across quantiles. The Penalty term is set to 1. For legibility considerations, bold coefficients indicate a statistical significance at the .05 level. The standard errors are obtained after 1000 panel bootstrap repetitions.

In the electronics industry (Table 5.5), the coefficients on exporting firms are positive at the lower end of the distribution, but turn negative at the upper ends of the distribution; firms benefit from innovative activities at each quantile of interest, but the coefficients at the lower ends of the distribution are statistically insignificant. The coefficients on subsidized firms turn positive and increase across the TFP distribution. This finding suggests that all firms benefit from direct state-subsidies, however, the high-productivity firms benefit more than low-productivity firms. A similar relationship exists for the coefficients on regional protectionism, although state subsidies are persistently negative across the TFP distribution.

In contrast to the agro-food processing and textiles industries, I find strong evidence for selection effects in both the agglomeration and industrial specialization variables in the electronics industry. For both variables, the high magnitude is concentrated at the lower ends of the distribution and diminish over time, becoming negative in the upper quantiles. The strong presence of selection revealed by the quantile regression results indicate that the positive effects of agglomeration on firm performance are overstated and partly driven by firm selection.

Interestingly, when I add the policy-concentration interaction term, evidence for selection disappears. In fact, the majority of quantiles return coefficients that are not statistically different from 0, while the upper 95th quantile is now statistically significant and positive. One interpretation of this finding is that state-protectionism removes the selection effect by preventing inefficient firms from exiting the market Despite policy distortions that mitigate the selection effect, I find that only the highest performing firms (top 5%) of state-favored firms located in concentrated regions benefit from localization economies spillovers.

5.5 Summary of Key Findings

Both localization economies and urbanization economies are generally found to improve firm production, but the relationship varies in intensity across industry. Similar to the recent findings from the 'new 'new' economic geography' literature (Baldwin and Okubo, 2006; Venables, 2011; Behrens and Duranton, 2010; Combes et al., 2012), the evidence reported in this paper confirms that firm selection drive, in part, the observed positive relationship between localization (urbanization) economies and firm productivity. The presence of sorting and selection effects bring into question whether the relationship between agglomeration and firm performance is as strong as originally thought for private Chinese firms. An interesting contribution of this paper based on the sectoral analysis reveals that the presence of firm selection and spatial sorting do not necessarily occur in tandem with each other, nor do they operate homogeneously across all economic activity; rather each process is industry specific and highly vulnerable to policy-induced distortions.

In regards to state-intervention, I find the effects of policy to be heterogeneous. In some cases, policy intervention instruments leads to inter-firm inequality by disproportionately benefiting high-productivity firms, while also directly harming under-performing firms' productivity. The mediating effects of policy are found to circumvent the selection effects in the electronics industry. The economic implications of this last finding reveals that state subsidies allow high-performing subsidized firms to outcompete foreign competitors, which helps the firms in the short-run. Conversely, the same state-intervention policies prevent inefficient low-performing firms from exiting the market, which leads to market distortions, leading to a non-competitiveness in the long-run.

From the model results, I find mixed evidence regarding the effects of policy on firm performance. Direct state subsidies generate higher levels of performance over time across the TFP distribution for firms in the electronics industry; although, such policies also result in exacerbating inter-firm inequality by disproportionately benefiting high-productivity firms. In terms of policy's mediating effect on the agglomeration-firm performance relationship, I find evidence in the textiles industry that state subsidies effectively encourage the lowest performing firms to become more competitive in agglomerative regions. This finding supports other empirical research that highlights the role of Chinese policy in spurring industrial catch-up (He and Qing, 2011). The same protectionist policy, however, is found to be ineffective at encouraging better performance for favored firms located in agglomerative regions in the agro-food processing and electronics industries.

I also find that state policy distorts both processes of firm selection and spatial sorting. For instance, in the electronics industry, I find that state-protectionism effectively undoes the natural Darwinian process of firm selection; thereby, preventing under-performing 'state-favored' firms from exiting the market. In the textiles industry, spatial sorting is exacerbated by state protectionist policies, indicating the coordination of high-productivity firms to locate within state-orchestrated industrial clusters.

5.6 Appendix

Table 5.6: Summary Statistics by Industry

Panel A: Agro-Food Processing

	Mean	St. Dev.	Min	Max
TFP	2.438	1.428	-8.583	8.023
Wage	1.287	1.178	0.0001	6.417
Size	128.396	203.945	1	3,110
Exp	0.163	0.369	0	1
Innov	0.060	0.238	0	1
Sub	0.104	0.305	0	1
Levrg	6.016	3.725	0.000	14.419
RegProt	9.038	0.374	6.080	10.400
StateProt	119.302	181.773	0.000	3,747.392
SPZ	0.027	0.161	0	1
Den	1.091	1.602	0.002	20.117
LQ	2.211	2.214	0.004	18.72

Panel B: Textiles

	Mean	St. Dev.	Min	Max
TFP	2.799	0.883	-8.786	8.750
Wage	1.501	0.951	0.0001	8.955
Size	224.799	323.610	1	3,096
Exp	0.324	0.468	0	1
Innov	0.066	0.248	0	1
Sub	0.108	0.311	0	1
Levrg	6.744	3.856	0.000	14.447
RegProt	9.091	0.317	6.080	10.400
StateProt	152.856	159.750	0.000	3,751.455
SPZ	0.025	0.155	0	1
Den	0.966	1.360	0.002	14.482
LQ	5.631	3.419	0.002	26.51

Panel C: Electronics

	Mean	St. Dev.	Min	Max
TFP	2.429	1.061	-8.658	7.948
Wage	2.071	1.130	0.002	8.389
Size	240.167	346.099	1	3,129
Exp	0.331	0.471	0	1
Innov	0.213	0.409	0	1
Sub	0.174	0.380	0	1
Levrg	7.193	4.223	0.000	15.585
RegProt	9.304	0.388	6.885	10.148
StateProt	323.532	445.438	0.000	8,653.734
SPZ	0.030	0.171	0	1
Den	0.651	0.943	0.033	13.824
LQ	4.658	3.712	2.002	13.490

Table 5.7: Pearson Correlation

	TFP	Wage	Size	Exp	Innov	Sub	TaxBr	Loans	RegProt	StProt	SPZ	Den
TFP												
Wage	0.36*											
Size	-0.02*	-0.14*										
Exp	0.04*	0.01*	0.23*									
Innov	0.04*	0.07*	0.16*	0.15*								
Sub	0.02*	0.06*	0.12*	0.03*	0.10*							
TaxBr	0.24*	0.20*	-0.21*	-0.18*	-0.04*	-0.03*						
Loans	0.11*	0.12*	-0.06*	0.10*	-0.02*	-0.03*	-0.03*					
RegProt	0.03*	0.09*	0.09*	0.14*	0.06*	0.04*	-0.14*	0.14*				
StProt	0.01	0.10*	0.01*	0.05*	0.10*	0.13*	-0.07*	0.03*	0.12*			
SPZ	0.00	0.00	0.03*	0.03*	0.00	0.00	-0.01*	-0.02*	-0.01	-0.01*		
Den	0.01	-0.07*	0.00	-0.07*	-0.01*	-0.02*	0.12*	-0.08*	-0.23*	-0.08*	0.01*	
LQ	0.00	0.08*	0.07*	0.20*	0.07*	0.03*	-0.17*	0.12*	0.38*	0.07*	0.02*	-0.15*

[1] Correlations are Pearson.

[2] $^{*}p < 0.001$

CHAPTER 6

A Structural Model of Innovation with Technological Learning, Knowledge Spillovers and Institutional Effects

6.1 Introduction

In the empirical literature, few studies offer representative analyses into the process of Chinese innovation and its impact on firm performance. Some relevant studies have begun to emerge in the English and Chinese language literatures that investigate the role of innovation on firm survival and success (Naidoo, 2010; Guan et al., 2009; Zhou, 2006; Tan, 2001). While these studies largely confirm a positive relationship between innovation and firm success, they tend to be small, cross-sectional case studies carried out in select cities. As a result, their findings are not necessarily generalizable across all Chinese cities or industries. Moreover, these studies do not adequately address the endogeneity issues related to measuring the effect of innovation on firm performance.

This chapter introduces a structural model that takes into account technological learning and knowledge spillovers to study the process of Chinese indigenous innovation and its impact on firm performance. The main advantages of the structural framework over previous approaches that examine the innovation-performance relationship, is that it corrects for the undesirable effects produced by selectivity and simultaneity bias (Lööf and Heshmati, 2006); moreover, it is parsimonious and empirically tractable (Griffith et al., 2006). Building on the structural model of innovation first proposed by Crépon et al. (1998), I extend the model to include multiple sources of technological learning, knowledge spillovers and institutional capacity.

Several potential sources of learning have been identified in the literature that can facilitate a firm's learning process (Zahra and George, 2002), which in turn can influence the process of innovation and firm performance (Cohen and Levinthal, 1990). Pertinent to the scope of this chapter, I first attempt to disentangle the sources of technological learning and the potential for learning spillovers by identifying multiple types of learning interaction effects that take place: (1) internal to the firm (learning by doing)[1]. ; (2) between the firm

[1] For the context of this chapter, the analysis of learning by doing is restricted to the firm-level, albeit

and environment (learning by export; and absorptive capacity of the firm to capture learning spillovers); and (3) external to the firm (learning spillovers mediated by institutional quality).

Following Crépon et al. (1998), I employ 3-Staged Least Squares – controlling for unobserved firm specific effects, reverse causation and endogeneity – to simultaneously estimate the effects of policy, learning interactions and knowledge spillovers on firm innovation and performance. Given some data limitations that do not include firm information on innovate inputs (i.e. R&D) before 2004, the present chapter relies on a balanced panel of 70,000 private Chinese firms operating in China from 2004-2007.

The outline of the paper is as follows. The next section introduces the structural framework, modeling strategy and variable development. Section 3 provides information on the summary statistics. Section 4 reveals the research findings from the structural model, and Section 5 provides an overview of the main findings and concludes with some final remarks.

6.2 Structural Model Specification

To estimate the model, I employ panel 3SLS with fixed effects to control for unobserved firm specific effects, simultaneity and endogeneity. This is a modest improvement over the original structural innovation framework – referred to as CDM – based on the seminal work by (Crépon et al., 1998) (and many of the related empirical works thereafter), which relies on cross-section data, and is thus, incapable of accounting for specific effects across firms. Similar to the CDM model, I assume innovation to be endogenous in the performance equation (iv), and R&D intensity to be endogenous in the innovation equation (iii). I develop proper instruments to further control for this endogeneity – firm's market share, distance to port, industry and year dummies[2]. The remaining explanatory variables are assumed to be

one prominent strand of the endogenous growth literature posits that learning by doing can also be observed and measured at the cluster or city level.

[2]The identification and use of proper instruments are noted as being notoriously difficult to find in the econometric literature. I follow Crépon et al. (1998) who were the first to use a firm's market share in their structural innovation models. Geographical distance variables have also been widely used as instruments for some time, especially in the growth literature. Although the development of the instruments used in this chapter are based on historical precedence, I also check to see whether the correlation between the excluded

exogenous, which is a difficult assumption to make. Therefore, when possible, the assumed exogenous variables are lagged by one year.

In line with Griffith et al. (2006), I estimate the CDM model for all firms, not just those with positive innovation sales. That is I estimate the R&D equations and use the predicted values for all firms as the proxy for the innovation effort in equation (iii). This approach departs from the majority of other studies and is based on the idea that all firms exert (imitative) innovative effort to some extent, but not all firms report their efforts (Griffith et al., 2006).

6.2.1 The Structural Equations

The set of four structural equations will first be introduced, along with the dependent variables and latent independent variables. Following the explanation of the models, the set of independent variables $\{X_i, Z_i, L_i\}$ will be explained and discussed. Lower case denotes logged values.

To obtain the innovation effort of the firm, I employ the estimation method developed by Wooldridge (1995) based on the Heckman two step-procedure (Heckman, 1976). In the first step, maximum likelihood is used to estimate the panel probit model with fixed effects – a firm's decision to invest in R&D (1=yes, 0=no). In the second step, pooled OLS is used to estimate the linear regression model for firms with a positive value of R&D with the dependent variable being the ratio of expenditures on research & development (R&D) to the number of employees.

The first equation relates to the decision to pursue innovation and the second equation relates to the intensity of resources – R&D – utilized in the innovation process. I assume g_i^* is the unobserved dependent variable for whether a firm invests in innovation and k_i^* is the latent or true intensity of a firm's investment in innovation, with g_i and k_i being their

instruments and the endogenous explanatory variables is strong enough to permit instrument identification. Indeed, after obtaining the first-stage Walds F-test statistic, I reject the weak instrument hypothesis.

observed counterparts. The first equation is defined as follows:

$$g_i = x_{i0}b_0 + z_{i0}\gamma_0 + l_{i0}\eta_0 + u_{i0} \tag{6.1}$$

and

$$k_i = x_{i1}b_1 + z_{i1}\gamma_1 + l_{i1}\eta_1 + u_{i1} \tag{6.2}$$

where x_{i0} and x_{i1} are vectors of firm characteristics, and b$_0$ and b_1 are their corresponding coefficient vectors. z_{i0} and z_{i1} represents the environmental conditions of the firm, with γ_0 and γ_1 as the associated vector coefficients. l_{i0} and l_{i1} are the learning interaction terms, and η_0 and η_1 are the associated vector coefficients. I assume marginal normality for u_0 and a linear conditional mean assumption for u_1.

In the innovation equation, I assume t_i^* is the latent dependent variable for innovation output based on the new product and process sales divided by the number of employees[3]. k_i^* is the predicted values for R&D obtained from equation 2. The equation can be expressed as follows:

$$t_i = \alpha_k k_i^* + x_{i2}b_2 + z_{i2}\gamma_2 + l_{i2}\eta_2 + u_{i2} \tag{6.3}$$

Total factor productivity (TFP) is used to measure firm performance, which assumes the contribution from technological progress or institutional change, and is the difference between output growth and the weighted average of the growth rate of input factors. To construct the TFP variable I follow Olley and Pakes (1996) semi-parametric approach, grouping firms into the same 2-digit industry to control for technological differences, and estimate TFP for each enterprise. t_i^* is the predicted value of innovation sales generated from equation 3 above

The performance equation is:

$$tfp_i = \alpha_I t_i^* + x_{i3}b_3 + z_{i3}\gamma_3 + l_{i0}\eta_3 + u_{i3} \tag{6.4}$$

[3]The literature discerns between two different types of innovation - new to the firm (imitation) vs. new to the market (true innovation). Unfortunately, our dependent variable does not distinguish between these two types of innovation, although as previously discussed, even for firms engaged in 'imitation' may benefit form the learning process involved with backward design strategies

6.3 Non-Parametric Results: Firm Innovation Activity

Table 6.1 presents the annual size-weighted means for the four key variables – firm choice to pursue innovation, R&D, Innovation Sales and TFP – used as our dependent variables in the structural model. The average percentage change in TFP from 2004-2007 is reported at just under 7%. R&D witnessed the highest average percentage change, increasing by 115% over the 2005-2007 period[4]. This large percentage change in R&D intensity is facilitated, in part, by the 40% increase in the number of firms that chose to invest in RD, as well as by firms investing a larger percentage of sales towards R&D activities.

Table 6.1: Structural Equations' Dependent Variables (size-weighted averages)

	2004	2005	2006	2007	AvgChge(%)
TFP	2.59	2.62	2.65	2.68	6.91
Innov	...	9.20	12.30	14.64	91.31
RDint	...	0.29	0.37	0.52	115.14
RDchoice	...	0.09	0.10	0.11	39.22

Table 6.2 reports a summary of firm persistence in R&D and innovation intensity over the 2005-2007 period. Less than 18% of firms report positive R&D sales and less than 17% report positive innovation sales. Of the firms engaged in innovative-related activities, 8.46% of firms engage in R&D activities and 6.81% report having new innovation sales for at least one of the observed periods. Slightly less than 1/2 of those respective firms report positive R&D expenditures and innovation sales for all 3 reporting periods.

Table 6.2: Innovation Activities of the Firm

Innovation Effort	N	Percent	Innovation Output	N	Percent
RD:3-yrs	2,999	4.38	Innov:3-yrs	2,569	3.76
RD:2-yrs	3,033	4.43	Innov:2-yrs	3,945	5.77
RD:1-yr	5,785	8.46	Innov:1-yr	4,660	6.81
RD:none	56,594	82.73	Innov:none	57,237	83.67
Total	68,411	100%	**Total**	68,411	100%

Table 6.3 reports the market share and size-weighted averages for TFP and innovation effort by industry. Textiles (12.5%) is the largest industry represented in the sample, fol-

[4] I do not have data on the innovation effort and innovation output for the year 2004

lowed by general equipment manufacturing (10.1%). Electrical machinery and equipment manufacturing observed the highest average TFP (3.9), as well as experienced the highest average percentage change (9.7%). Pharmaceutical manufacturing reported the highest average innovation sales (35.5), followed by instruments, meters, and office machinery (33.7) and communications, computers and electronics (31.5). The fastest movers in innovation output occurs in the resource intensive industries, nonferrous metal smelting and processing (158%) and wood processing (149%). Interestingly, all industries reported positive changes in innovation output, indicating a growing reliance on developing new product or processes.

Table 6.3: Industrial Performance and Innovation Characteristics, 2004-2007

SIC	Industry	Firms	TFP	% ΔTFP	Innov	% $\Delta Innov$
13	Agro-food processing	2.1	2.4	2.4	4.1	34.8
14	Food manufacturing	1.8	1.1	−6.8	11.9	35.9
15	Beverage manufacturing	1.1	1.2	−2.4	10.7	116.8
17	Textiles	12.5	2.8	0.2	8.9	104.9
18	Textiles, garments, shoes, and hat manufacturing	3.8	3.1	4.5	5.3	17.1
19	Leather, fur, feather products	2	2.5	2.2	7.8	120.9
20	Wood processing/wood, bamboo, rattan, brown, grass products	2.8	1.8	11	7.3	149.8
21	Furnish Making	1.3	2.5	1.6	8.7	88.4
22	Paper/Paper products	3.7	2.1	1.1	4.8	40.1
23	Printing/record medium reproduction	2	1.2	−10.3	9.5	17.9
24	Educational/sports goods	1.1	3.5	4.8	9.3	34.6
26	Chemical materials/chemical products	7.2	2.4	1	14.7	30.6
27	Pharmaceutical manufacturing	1.8	1.5	0.7	35.5	51
28	Chemical fiber	0.5	2.9	−3.5	6.6	48.6
29	Rubber products	1.4	2.3	4.3	7.6	58.8
30	Plastic products	5.4	2.8	1.3	9.9	66.5
31	Nonmetallic mineral products	8.8	2.5	4.2	7.8	42.7
32	Ferrous metal smelting/rolling processing	2.1	1.9	8.7	5.9	70.3
33	Nonferrous metal smelting/rolling processing	0.3	2.8	−9.9	9.4	158.2
34	Metallic mineral products	6.6	2.8	2.6	9.0	50.5
35	General equipment manufacturing	10.1	3.0	4.8	12.2	72.1
36	Special equipment manufacturing	4.5	3.1	5	21.9	82.5
37	Transportation equipment	4.9	2.1	2.7	17.5	64.8
39	Electrical machinery and equipment manufacturing	6.9	3.9	9.7	21.5	73.2
40	Communications equipment, computers/other electronic equipment	2.4	2.2	6	31.5	55.1
41	Instruments, meters, cultural and office machinery	1.3	2.8	1.7	33.7	68
42	Artwork/other manufacturing	1.7	3.5	2.8	7.8	124.4

Figures 6.3 and 6.4 plot the respective size-weighted average change (ln) for innovation and TFP by city. Both maps show a predominant concentration of innovative activity and high TFP along the coastal region of China, while the interior lags behind on both accounts. Although clusters of innovation can be identified along the coast, innovative activity appears to be diffusing throughout the coastal and central regions of China. In contrast, the highest levels of TFP change occur in a much more concentrated pattern, with little to no indication that central and western regions enjoy high TFP levels.

6.4 Parametric Results: A Structural Approach

In the Baseline model I am most interested in the role of LBD (proxied by age), absorptive capacity of the firm (AbsCap), export intensity (Exp), learning spillovers (EG3 and Labor density) and institutional effects at each stage of the innovation. To take into account learning interaction effects, additional models are subsequently estimated. See Table 6.7 and 6.8 in the appendix for the summary statistics and Pearson's correlation coefficients, respectively.

The Learning I model offers an improved proxy for LBD by interacting firm experience in years with its previous year's labor productivity (learning interaction internal to the firm). The Learning II model further examines the potential for learning spillovers conditioned on the firm's absorptive capacity (firm- environment learning interaction). The Learning III model adds an additional interaction term for learning spillovers mediated by institutions (learning interaction external to firm). Each of the four model specifications are briefly discussed for each stage of the innovation process.

6.5 Model Empirics: Structural Equations

6.5.1 Innovation Effort Equations

The R&D equations relate to the firm's innovation effort (Table 6.4). I find that firms with larger market shares are more likely to choose to innovate. Distance (in Km) from the port

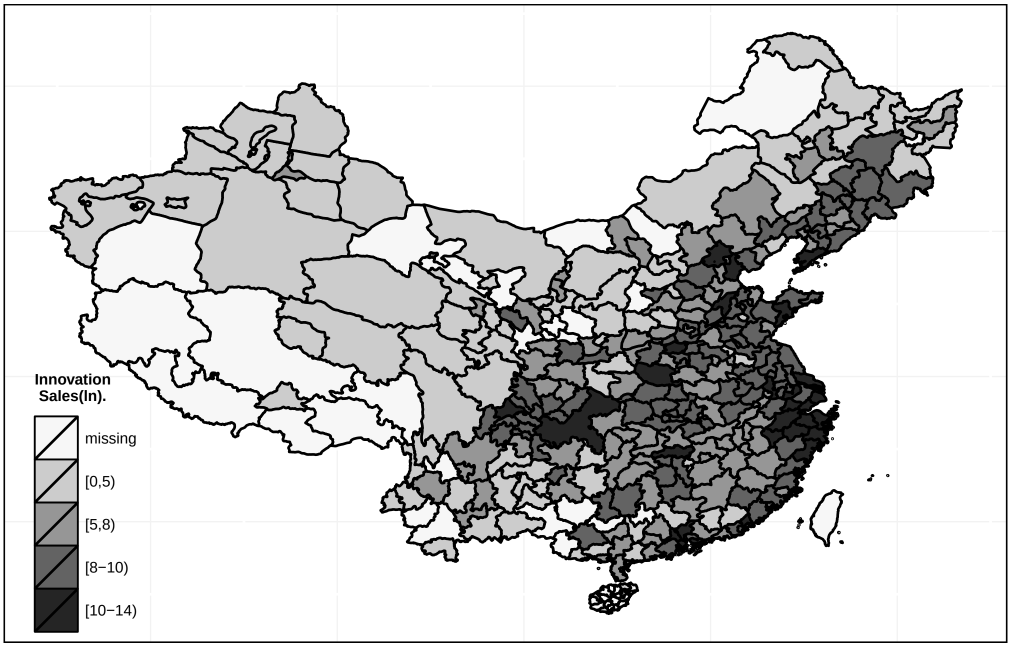

Figure 6.1: Innovation Sales (Ln), 2005-2007

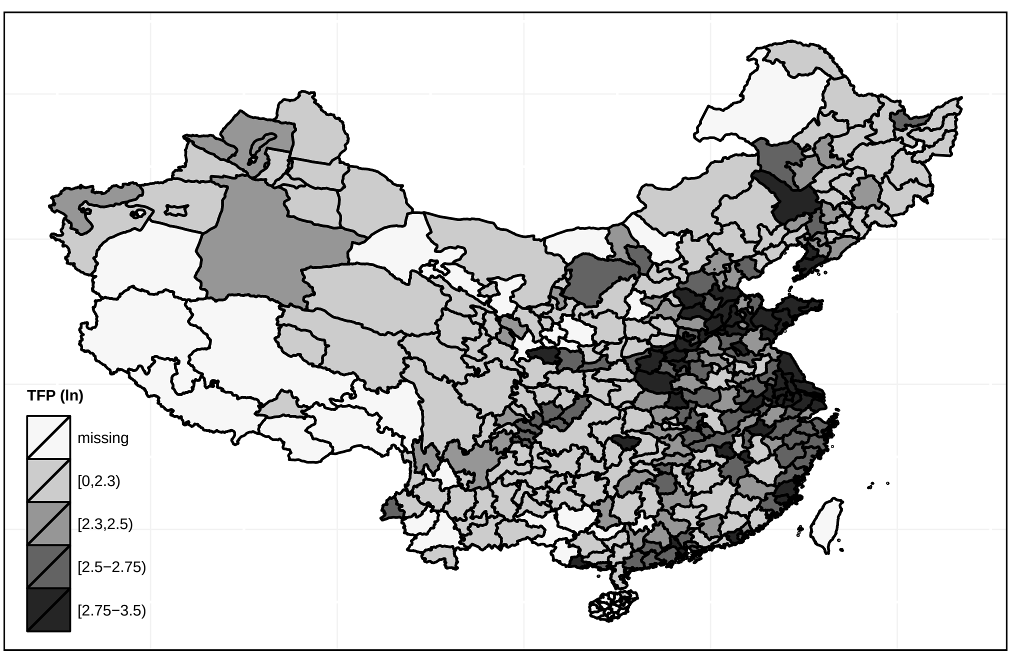

Figure 6.2: TFP (Ln), 2004-2007

(i.e. access to foreign knowledge proxy) does not affect decision to innovate, but the larger distance tends to reduce R&D intensity.

Older firms are more likely to choose to innovate, but younger firms pursue a more intensive innovative strategy. Allowing for non-linear effects of experience, I find the opposite relationship. The most experienced firms are less likely to choose to innovate, but pursue more intensive innovation strategies. This result is confirmed in three of the four models, and provides mixed results with regards to LBD expectations.

Absorptive capacity plays a positive role in the firm's decision to both choose to innovate and in intensity of R&D activities. The higher the export intensity the more likely to choose to innovate. Direct subsidies both increase the likelihood of choosing to innovate and increase R&D intensity. Higher debt-to-equity (leverage) increases likelihood a firm will choose to innovate, but reduces R&D intensity.

Interestingly, industrial specialization does not impact the choice to innovate nor the R&D intensity, whereas labor density increases the likelihood a firm will choose to innovate, but leads to lower levels of R&D intensity. State Industrial subsidies increases both the probability that a firm will choose to innovate, as well as increase the R&D intensity. On the other hand, regional protectionism does not impact the choice to innovate, and is found to negatively impact R&D intensity. The quality of institutions increases both the decision to innovate, as well as the R&D intensity.

In the subsequent models - Learning I, II, and III - I add the learning interaction terms. Learning by doing diminishes the need for firms to invest in innovative activities, yet firms able to benefit from learning by doing will dedicate a larger amount of resources towards R&D intensity. Conversely, learning by exporting is found to not affect the choice to innovate, and reduces R&D intensity.

The higher the firm's ability to absorb knowledge from spatial externalities reduces its likelihood of choosing to carry out internal R&D in the case of knowledge generated from industrial specialization, and will reduce the R&D intensity in the case of knowledge generated from labor density. The role of building strong institutions play an important role

Table 6.4: RD Equations

	Baseline		Learning I		Learning II		Learning III	
	Probit	Tobit	Probit	Tobit	Probit	Tobit	Probit	Tobit
(Intercept)	-1.687^{***}	0.271^{***}	-1.460^{***}	0.119^{***}	-1.457^{***}	0.112^{***}	-1.437^{***}	0.113^{***}
	(0.139)	(0.018)	(0.139)	(0.018)	(0.139)	(0.018)	(0.139)	(0.018)
Mrktshr	0.221^{***}	...	0.268^{***}	...	0.267^{***}	...	0.267^{***}	...
	(0.004)	...	(0.005)	...	(0.005)	...	(0.005)	...
DistPrt	0.005	-0.002^{***}	0.000	-0.001^{***}	0.000	-0.001^{**}	-0.002	-0.001^{**}
	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
Age	0.139^{*}	-0.007	0.482^{***}	-0.049^{***}	0.481^{***}	-0.049^{***}	0.482^{***}	-0.049^{***}
	(0.059)	(0.007)	(0.062)	(0.007)	(0.062)	(0.007)	(0.062)	(0.007)
Age2	0.005	0.001	-0.035^{*}	0.006^{***}	-0.037^{*}	0.007^{***}	-0.036^{*}	0.007^{***}
	(0.015)	(0.002)	(0.015)	(0.002)	(0.015)	(0.002)	(0.015)	(0.002)
AbsCap	1.393^{***}	0.353^{***}	1.464^{***}	0.392^{***}	1.581^{***}	0.458^{***}	1.547^{***}	0.458^{***}
	(0.042)	(0.007)	(0.042)	(0.007)	(0.076)	(0.012)	(0.076)	(0.012)
Exp	0.422^{***}	-0.022^{***}	0.344^{***}	0.008^{*}	-0.031	0.105^{***}	-0.046	0.105^{***}
	(0.028)	(0.004)	(0.029)	(0.004)	(0.200)	(0.028)	(0.200)	(0.028)
Subs	2.785^{***}	0.288^{***}	2.734^{***}	0.411^{***}	2.738^{***}	0.413^{***}	2.719^{***}	0.411^{***}
	(0.143)	(0.022)	(0.143)	(0.022)	(0.143)	(0.022)	(0.143)	(0.022)
Levg	0.293^{***}	-0.023^{***}	0.236^{***}	-0.001	0.236^{***}	-0.001	0.239^{***}	-0.001
	(0.048)	(0.006)	(0.049)	(0.006)	(0.049)	(0.006)	(0.049)	(0.006)
EG3	0.286	-0.046	0.089	-0.014	0.219	-0.021	0.167	-0.019
	(0.242)	(0.031)	(0.243)	(0.031)	(0.245)	(0.032)	(0.245)	(0.032)
Den	0.052^{***}	-0.012^{***}	0.051^{***}	-0.009^{***}	0.052^{***}	-0.008^{***}	0.065^{***}	-0.008^{***}
	(0.011)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)
IndProt	0.041^{***}	0.005^{***}	0.055^{***}	0.005^{***}	0.055^{***}	0.005^{***}	0.056^{***}	0.005^{***}
	(0.009)	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)	(0.009)	(0.001)
RegProt	0.008	-0.009^{***}	0.018	-0.010^{***}	0.018	-0.010^{***}	0.020	-0.010^{***}
	(0.012)	(0.001)	(0.012)	(0.002)	(0.012)	(0.002)	(0.012)	(0.002)
InstQ	0.022^{***}	0.002^{**}	0.023^{***}	0.002^{***}	0.023^{***}	0.002^{***}	0.077^{***}	0.000
	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.008)	(0.001)
LrnDo	...	...	-0.105^{***}	0.015^{***}	-0.105^{***}	0.015^{***}	-0.106^{***}	0.015^{***}
	...	...	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
LrnExp	...	...	...	...	0.338	-0.069^{**}	0.358^{*}	-0.069^{**}
	...	...	...	...	(0.179)	(0.021)	(0.179)	(0.021)
AbsCap*EG3	...	...	...	...	-6.127^{**}	0.204	-5.979^{**}	0.183
	...	...	...	...	(1.990)	(0.283)	(1.991)	(0.283)
AbsCap*Den	...	...	...	...	0.018	-0.184^{***}	0.073	-0.185^{***}
	...	...	...	...	(0.133)	(0.020)	(0.133)	(0.020)
EG3*InstQ	...	...	...	...	...	...	-0.219	0.087^{***}
	...	...	...	...	...	...	(0.198)	(0.026)
Den*InstQ	...	...	...	...	...	...	-0.099^{***}	0.001
	...	...	...	...	...	...	(0.011)	(0.001)
IMR	-0.102^{***}	...	-0.154^{***}	...	-0.102^{***}	...	-0.101^{***}	...
	(0.003)	...	(0.003)	...	(0.003)	...	(0.003)	...
Adj. R^2	...	0.122	...	0.119	...	0.119	...	0.119
Num. obs.	205233	205233	205233	205233	205233	205233	205233	205233
Num. Firms	68411	68411	68411	68411	68411	68411	68411	68411
LL	...	-60777.6	...	-60593.3	...	-60583.8	...	-60546.6

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

in providing confidence to firms to combine knowledge absorbed from spatial externalities with internal R&D expenditures. In other words, firms that are specialized and located in a region with strong institutions leads to higher R&D intensity.

6.5.2 Innovation Output Equation

In all four models, R&D intensity increases innovative output (Table 6.5). With regards to firm experience, I find older firms are less likely to innovate, although this effect is non-linear indicating that the oldest firms are associated with higher levels of innovation output. The absorptive capacity of the firm is found to statistically increase innovation output in all four models. Export intensity is also found to be positively associated with innovation output for all three models. The financial structure of the firm plays an important role on innovation. Both direct subsidies and access to loans leads to positive effects on innovation.

Both industrial specialization and labor density are found to lead to increased innovation output, although industrial specialization plays a much stronger role in facilitating knowledge spillovers. Interestingly, industrial protectionism does not persist through the innovation effort stage, having no effect on innovation output. Regional protectionism on the other hand remains significant, increasing innovative output.

Institutional quality does not impact innovation output, except in the last model. One way to understand this finding is that in order for policy and infrastructure to have a positive effect on innovation, the enterprises within a particular region must have the appropriate absorptive capabilities and resources (Guan et al., 2009). The statistically negative coefficient in the last model should be interpreted with caution, considering it only becomes significant when the interaction term with institutions is entered in the model.

The models Learning I, II, and III add the learning interaction effects. I find that learning by doing leads to higher innovation output in all 3 models. Learning by export remains insignificant. The role of spatial externalities is further mediated by institutional quality. Firms located in specialized industries and supported by strong local institutions will generate higher levels of innovative output.

Table 6.5: Innovation Equations

	Baseline	**Learning I**	**Learning II**	**Learning III**
(Intercept)	1.106***	1.098***	1.109***	1.105***
	(0.086)	(0.086)	(0.086)	(0.086)
RDint	1.404***	1.370***	1.368***	1.368***
	(0.012)	(0.012)	(0.012)	(0.012)
Age	−0.112**	−0.270***	−0.270***	−0.270***
	(0.037)	(0.038)	(0.038)	(0.038)
Age2	0.047***	0.067***	0.066***	0.066***
	(0.010)	(0.010)	(0.010)	(0.010)
AbsCap	0.286***	0.267***	0.809***	0.815***
	(0.035)	(0.035)	(0.062)	(0.062)
Exp	0.677***	0.699***	0.631***	0.629***
	(0.020)	(0.020)	(0.154)	(0.154)
Subs	1.017***	1.062***	1.055***	1.054***
	(0.114)	(0.114)	(0.114)	(0.114)
Levg	0.144***	0.156***	0.158***	0.157***
	(0.033)	(0.033)	(0.033)	(0.033)
EG3	1.354***	1.430***	1.345***	1.370***
	(0.171)	(0.171)	(0.172)	(0.172)
Den	0.087***	0.087***	0.102***	0.101***
	(0.007)	(0.007)	(0.007)	(0.007)
IndProt	0.002	−0.001	−0.001	0.000
	(0.006)	(0.006)	(0.006)	(0.006)
RegProt	0.106***	0.106***	0.108***	0.108***
	(0.008)	(0.008)	(0.008)	(0.008)
InstQ	0.000	0.000	0.000	−0.017**
	(0.003)	(0.003)	(0.003)	(0.005)
LrnDo	...	0.045***	0.045***	0.045***
	...	(0.003)	(0.003)	(0.003)
LrnExp	...	...	0.186	0.188
	...	...	(0.116)	(0.116)
AbsCap*EG3	...	...	6.451***	6.263***
	...	...	(1.545)	(1.545)
AbsCap*Den	...	...	−1.704***	−1.709***
	...	...	(0.108)	(0.108)
EG3*InstQ	...	...	...	0.656***
	...	...	...	(0.142)
Den*InstQ	...	...	...	0.011
	...	...	...	(0.008)
Adj. R^2	0.089	0.090	0.092	0.092
Num. obs.	205233	205233	205233	205233
Num. Firms	68411	68411	68411	68411

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Firms with higher absorptive capacity are positively mediated by industrial specialization. Surprisingly labor density is found to have negative mediating effects on a firm's absorptive capabilities. One explanation for this unlikely finding lays in the construction of the absorptive capacity variable, which itself is interacted by the proportion of professional staff in 2004 by the annual amount of spending on professional training from 2005-2007. A possible interpretation of the coefficient is that urbanization economies leads to higher levels of innovation for low-skilled, labor- intensive firms. This finding is consistent with the innovative manufacturing perspective that even in remedial tasks, such as assembly, Chinese firms create new processes or products to reduce costs.

6.5.3 Firm Performance Equation

Innovation intensity is statistically significant and leads to higher TFP performance in all four models (Table 6.6). Similar to the Innovation equation, I find the same non-linear relationship between firm age and TFP. As firms age they tend to be less productive, but the most mature firms remain the most productive. The absorptive capacity of the firm is statistically significant and positive in the Baseline and Learning I models, but becomes insignificant once the learning interaction terms are included in Learning II and III models.

The role of exports on firm performance remains a puzzle. In the baseline model, export intensity decreases TFP output, but is found to increase TFP when the learning by doing interaction term is included in the model, and then becomes insignificant once the other learning and institutional interaction terms are included. One interpretation of this finding suggests that exporting firms that exhibit learning by doing are able to become more productive than exporting firms that fail to learn from their experiences.

Unlike in the innovation effort stage, subsidized and indebted firms experience lower levels of TFP. Similarly, industrial specialization is found to diminish TFP in the baseline model, but becomes insignificant in the subsequent models. The statistically significant negative coefficient in the baseline model, likely reflects the 'competition effect' generated by industrial specialization, which leads to greater entry-rates and lower productivity output.

Table 6.6: TFP Equations

	Baseline	**Learning I**	**Learning II**	**Learning III**
(Intercept)	0.694***	0.730***	0.603***	0.611***
	(0.029)	(0.025)	(0.035)	(0.035)
Innov	0.115***	0.031***	0.088***	0.085***
	(0.005)	(0.005)	(0.014)	(0.014)
Age	−0.011	−0.779***	−0.781***	−0.781***
	(0.012)	(0.011)	(0.011)	(0.011)
Age2	0.013***	0.109***	0.110***	0.110***
	(0.003)	(0.003)	(0.003)	(0.003)
AbsCap	0.171***	0.030**	−0.008	−0.001
	(0.011)	(0.010)	(0.019)	(0.019)
Exp	−0.114***	0.015*	−0.004	−0.002
	(0.007)	(0.006)	(0.045)	(0.045)
Subs	−0.654***	−0.464***	−0.459***	−0.453***
	(0.038)	(0.034)	(0.034)	(0.034)
Levg	−0.176***	−0.110***	−0.109***	−0.109***
	(0.011)	(0.010)	(0.010)	(0.010)
EG3	−0.275***	0.082	0.076	0.087
	(0.056)	(0.050)	(0.050)	(0.050)
Den	0.049***	0.054***	0.054***	0.052***
	(0.002)	(0.002)	(0.002)	(0.002)
IndProt	−0.003	−0.018***	−0.018***	−0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
RegProt	−0.009***	0.000	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
InstQ	0.030***	0.031***	0.031***	0.021***
	(0.001)	(0.001)	(0.001)	(0.002)
LrnDo	...	0.215***	0.215***	0.215***
	...	(0.001)	(0.001)	(0.001)
LrnExp	...	...	0.020	0.018
	...	...	(0.034)	(0.034)
AbsCap*EG3	...	...	1.038*	0.995*
	...	...	(0.451)	(0.451)
AbsCap*Den	...	...	0.048	0.039
	...	...	(0.032)	(0.032)
EG3*InstQ	...	...	...	0.093*
	...	...	...	(0.042)
Den*InstQ	...	...	...	0.019***
	...	...	...	(0.002)
Adj. R^2	0.327	0.468	0.468	0.468
Num. obs.	205233	205233	205233	205233
Num. Firms.	68411	68411	68411	68411

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Labor density is found to increase TFP output in all model estimations. State industrial protection is found to reduce TFP and is significant in 3 of the 4 models. Likewise, regional protectionism also harms TFP output, but is significant in only the baseline model. Quality institutions positively impact TFP performance and is significant in all 4 models.

Including the learning interaction terms, I find that learning by doing leads to higher levels of TFP, whereas there is no evidence to suggest that learning by exporting leads to increased TFP. Although industrial specialization (above) resulted in lower TFP output, I find that firm with a high-skilled labor force will absorb intra-industry knowledge spillovers, which in turn increases TFP performance. There is no evidence to suggest that labor density interacted with the absorptive capacity of the firm impacts TFP. In the Learning III model, I find that institutional quality positively mediates both industrial specialization and labor density, leading to higher levels of TFP.

6.6 Summary of Key Findings

The structural framework introduced in this paper provides deep insight into the mediating effects of firm learning, learning spillovers and institutions on Chinese innovation and firm performance. I find that firms that do engage in indigenous research and development increase their innovative throughput, which in turn, is found to increase firm performance. I also find evidence that supports the positive effects of learning by doing at each stage of the model; conversely I do not find any evidence to suggest that firms learn by exporting. The lack of learning by exporting supports previous studies that bring into question the effectiveness of China's market-access-for-foreign-capital strategy (Young and Lan, 1997; Cheung and Lin, 2004), as domestic Chinese firms do not appear to benefit from their interactions with foreign buyers' technical and managerial expertise.

In the early stages of innovation, I find little evidence to suggest that Chinese firms are capturing learning spillovers and incorporating them into their innovation effort, even when the firm's absorptive capacity is taken into account. Conversely, in the later stages of innovation, learning spillovers are found to positively increase the firm's innovation output, as well as its performance, especially for firms with high absorptive capacity. This result confirms previous work that suggests that the effects of learning spillovers on innovation vary according to the stage of innovation (Ghemawat and Spence, 1985; Barrios and Strobl, 2004): the presence of learning spillovers reduces the firm's incentives to invest in innovation – in-house R&D, yet leads to higher levels of innovation output – imitation, and enhances firm productivity.

Lastly, I find that state and local policy instruments and the role of institutions potentially play important roles in fostering (obstructing) innovation in China, as they can help facilitate (hinder) firms' ability to capture and integrate learning spillovers with in-house innovation efforts. In support of state-intervention, protective policy measurements at both the state and local levels are found to spur the short-run innovation effort; although the same protectionist policy measures are found to reduce innovation output and hamper firm performance outcomes in the long-run. These results suggest that developing institutional norms and rule of law may substitute the need for strong state and local intervention; which in turn, would encourage the process of innovation in China to conform to the logic of the market.

To become a global "innovative powerhouse," the results presented in this chapter highlight the importance of institution building, along with contemporaneous efforts to reduce the role of state and local governments in the market. Building a solid institutional environment reduces the high risks associated with pursuing innovation and will help facilitate the transferring of tacit knowledge leading to both intra- and inter-industrial spillovers, thereby reducing firm dependency on state protectionism, and spurring firm competitiveness. Combined with the limited, strategic policy instruments and further accumulation of learning by doing, Chinese firms will better absorb learning spillovers and integrate them with in-house R&D activities. In time, it is likely that China will continue to contribute widely to the global stock of knowledge and increase its value-added at all points of the global production chain.

6.7 Appendix

Table 6.7: Summary Statistics

	Mean	St. Dev.	Min	Max
TFP	2.685	0.978	0.0002	12.610
Innov	12.566	77.933	0.000	3,701.362
RDint	0.489	3.613	0.000	214.857
RDch	0.102	0.302	0	1
Mktshr	0.280	0.365	0.001	4.672
DistP	347.587	308.231	0.000	2,732.400
Age	6.716	3.511	1	17
Exp	0.094	0.244	0.000	1.000
Sub	0.005	0.026	0.000	0.355
Levrg	0.035	0.096	0.000	0.763
AbsCap	0.012	0.078	0.000	3.242
EG3	0.016	0.017	-0.014	0.151
Den	0.754	1.093	0.002	11.196
IndPr	175.633	127.422	2.939	1,850.756
RegPr	0.000	1.000	-1.956	22.122
InstQ	0.000	1.000	-0.961	10.130
LrnDo	10.571	3.070	1.118	23.658

Table 6.8: Pearson Correlation

Panel B: Correlations

	TFP	Innov	RDint	RDch	Mktshr	DistP	Age	Exp	Subs	Levg	AbsCap	EG3	Den	IndPr	RegPr
TFP															
Innov	0.07*														
RDint	0.05*	0.28*													
RDch	0.03*	0.18*	0.40*												
Mktshr	0.22*	0.05*	0.01*	0.10*											
DistP	-0.06*	0.01	-0.02*	0.02*	0.00										
Age	0.06*	0.02*	0.03*	0.07*	0.10*	-0.02*									
Exp	0.03*	0.03*	-0.01*	0.03*	0.09*	-0.11*	0.06*								
Subs	-0.04*	0.03*	0.05*	0.05*	0.00	0.03*	0.03*	-0.01*							
Levg	-0.05*	0.00	-0.01	0.01*	0.03*	0.08*	0.01*	-0.04*	0.01*						
AbsCap	0.05*	0.08*	0.17*	0.14*	0.02*	0.02*	0.02*	-0.03*	0.02*	0.00					
EG3	-0.01*	0.02*	0.01*	0.03*	0.01*	0.02*	0.03*	0.07*	0.00	-0.01*	0.00				
Den	0.04*	-0.02*	-0.02*	-0.01*	0.03*	0.09*	0.00	-0.03*	-0.03*	0.02*	-0.02*	-0.03*			
IndPr	-0.11*	0.03*	0.05*	0.06*	-0.06*	0.11*	-0.01*	-0.14*	0.11*	0.07*	0.05*	0.06*	0.00		
RegPr	-0.03*	-0.01	-0.05*	-0.02*	-0.03*	0.05*	-0.07*	0.05*	0.00	0.02*	-0.08*	0.01	0.18*	0.02*	
InstQ	-0.04*	0.01	0.01*	0.02*	-0.03*	0.45*	-0.10*	-0.13*	0.03*	0.07*	0.02*	-0.03*	0.06*	0.14*	0.04*

[1] Correlations are Pearson.
[2] $^{*}p < 0.001$

CHAPTER 7

Conclusion

In the wake of the 2008-09 global financial crisis, China and other dirigisme-based Asian economies recovered quicker than Western liberal capitalist economies. Their resilience to the economic downturn has attracted growing interest from world leaders, policy makers and scholars, leading some observers to speculate that state-capitalism may provide a superior alternative to liberal capitalism (Lin, 2011; Herman, 2012). In support of this view, successful companies like Samsung, Hyundai, and LG (S. Korea), Foxconn (Taiwan) and Huawei (Mainland China), all demonstrate that firms with close connections with the state government can become strong innovators and accumulate large profits.

Despite such speculation and anecdotal evidence, the statistical and representative evidence presented in this research draws into question the sustainability of persistent state-intervention in the Chinese economy. In this dissertation, the heterogeneous short- and long-run impacts of policy-induced economic distortions are respectively evaluated within three separate relationships to firm performance: (1) innovation; (2) agglomeration; and (3) a geo-economic innovation framework. The unifying theme that emerges from the results reveals that state-intervening policies distort the economy in terms of all three relationships.

A key finding from Chapter 4 indicates that the spatial scale of state-protectionism affects innovative firms in substantially different ways compared to non-innovative firms. While I do find clear evidence that suggests short-run benefits exist for direct, local and state protectionism on firm survival, I find that too much direct intervention, i.e. highly subsidized and over-leveraged firms, leads to lower chances of firm survival. Moreover, in the long-run, I find that both local and state protectionism harm survival rates for innovative firms.

Based on these findings, I conclude that the riskiness associated with pursuing innovative activities increases in the presence of prolonged state-protectionism, which tends to harm innovative firms in the long-run. One reason for this is because innovative firms must direct much time and resources to develop a successful innovation strategy, yet because they operate in a non-competitive environment they are prevented from accumulating the benefits, such as market dominance, normally derived from innovation in a competitive, market economy. These findings confirm the liberal-capitalist expectations that state protectionism delays prolong inefficient firms from exiting the market, thereby diminishing competition, which in turn, leads to unfavorable outcomes for innovation and firm performance.

Other key findings from Chapter 4 point to progressive steps made by China to transition from a command economy to a market-led economy. Similar to the findings in Western, advanced capitalist countries, I find that innovation is one of the most influential factors in determining the duration of a firm. Building a successful innovative strategy, therefore is of utmost importance for firms to remain competitive in the Chinese market, avoid spells of financial distress and extend duration periods. While this result is encouraging, it is unfortunate that the previous findings on the impacts of local and state protectionism may undermine some of these benefits that would normally be accrued to innovative firms in a more competitive, market-oriented economy.

In Chapter 5, I examine the agglomeration-firm performance relationship in the presence of economic distortions for three very important industries in China. I discern whether firms' increased productivity gains are the result of positive externalities or due to other competing explanations developed in the recent literature, mainly that of spatial sorting and firm selection. As part of the empirical strategy I introduce a new FE quantile regression approach to examine the effects of policy distortions on firm performance and the agglomeration-sorting-selection processes. Overlapping with results generated in the general literature (Segal, 1976; Ciccone and Hall, 1996; Henderson, 2003; Brülhart and Mathys, 2008), I find a positive relationship between localization economies and firm productivity in all three industries of analysis. Urbanization economies is also found to influence firm productivity in both textiles and electronics industries, but is insignificant in agro-food processing industry. In all three industries, the impact of urbanization economies on firm performance is negligible compared to the effects of localization economies.

In regards to policy, direct state-subsidies act as a source of inter-firm inequality in electronics by disproportionately benefiting high-productivity firms, although in the textiles industry, direct state subsidies appear to be promoting the performance of low-performing firms. Results also indicate that local forms of protectionism lead to unwanted negative outcomes on firm performance. Posited within the larger changing economic reforms in China, the finding highlights one of the adverse effects of China's administrative decentralization and devolution of power from the state to regional authorities (Wei, 2000; He, 2009).

In terms of policy's mediating effect on the agglomeration-firm performance relationship, I find evidence in the textiles industry that state subsidies effectively encourage the lowest performing firms to become more competitive in agglomerative regions. This finding supports other empirical research that suggests the role of Chinese policy on spurring industrial catch-up (He and Qing, 2011). The same protectionist policy, however, is found to be ineffective at encouraging better performance for favored firms located in agglomerative regions in the agro-food processing and electronics industries.

I also find that state policy distorts both processes of spatial sorting and firm selection. In the electronics industry, I find that state-protectionism effectively undoes the natural Darwinian process of firm selection; thereby, preventing under-performing 'state-favored' firms from exiting the market. In the textiles industry, spatial sorting is exacerbated by state protectionist policies, indicating the coordination of high-productivity firms to locate within state-orchestrated industrial clusters.

One of the main contributions derived from the empirical strategy links recent developments made in the 'new 'new' economic geography with the policy-agglomeration literature. Similar to the recent findings from the 'new 'new' economic geography' literature (Baldwin and Okubo, 2006; Venables, 2011; Behrens and Duranton, 2010; Combes et al., 2012), the evidence reported in Chapter 5 confirms that both spatial sorting and firm selection drive, in part, the observed positive relationship between localization (urbanization) economies and firm productivity. The sectoral analysis reveals that the presence of spatial sorting and firm selection do not necessarily occur in tandem with each other, nor do they operate homogeneously across all economic activity; rather each process is industry specific and highly vulnerable to policy-induced distortions.

In Chapter 6, I incorporate technological learning and knowledge spillovers into a structural model of innovation, leading to a 'geo-economic' model of innovation that is capable of examining the linkages among innovation, agglomeration and firm performance. The geo-economic model of innovation offers new insight into the mediating effects of firm learning, learning spillovers and institutions on Chinese innovation and firm performance.

Results reveal that private Chinese firms that have the capacity to absorb the knowledge generated by spatial externalities and learning choose, in general, to not integrate that knowledge with in-house R&D activities. In view of the firm's inability or unwillingness to integrate learning spillovers with pursuing indigenous innovation strategies, the role of the state becomes particularly important. The state plays a key role in encouraging firms to pursue innovation through various policy tools, including subsidies for firms that open R&D labs, tax breaks and unfettered access to loans, especially for firms in strategic industries. From this perspective, industrial policy and local protectionism work to minimize the high-risks associated with pursuing innovation, as well as mitigate the negative effects of potential market failures that disrupt the transfer of tacit knowledge from the environment to the firm.

Similar to the findings presented in Chapter 4, I find that these interventionist policies in the early stages of the innovation effort lead to unwanted consequences that tend to hurt the overall innovation climate at later stages and ultimately diminish firm performance. This outcome reflects the conventional neoliberal view that strong state-interventionism distorts market conditions and reduces firm competition. One explanation for this outcome is because protected firms maintain a close relationship to the Chinese state and have unfettered access to state finance with little to no state oversight (Huang, 2003), engendering a world of survival certainty. Because these favored firms are insulated from outside competition, they are deprived of the incentives to innovate and upgrade their technological systems (Fuller, 2008).

Likewise, non-favored firms are also less likely to take on the costs of innovation, including patent applications, commercialization, advertising, and so forth, if they are unable to capitalize on the associated benefits of innovation, nor gain a competitive advantage, in the presence of inefficient and non-competitive markets. If entrepreneurs believe that their relationship to the state is the most important predictor of their success, they will spend more time and energy on developing political networks, as opposed to investing in innovation. In this respect, the state-market relationship diminishes the returns to Chinese innovation

(Park and Luo, 2001).

Additional results from Chapter 6 suggest that developing institutional norms and rule of law may substitute for the need for strong state and local intervention; which in turn, would encourage the process of innovation in China to conform to the logic of the market. In the innovation effort model, the positive coefficient on institutional quality indicates that firms with positive institutional environments will choose to pursue, and pursue more intensively, innovation-related activities. Similarly, institutions are found to positively mediate intra-industrial learning spillovers in the innovation effort, and positively mediate both intra- and inter-industrial learning spillovers for firm performance.

Taken together, the results reflect the bipartite system in China that is characterized by dual, self-reinforcing market-led principles occurring in tandem with state directives. Evidence suggests that China's transition towards a market-oriented economy has firmly taken root, creating in some respects, similar firm dynamics as those operating in other countries. As China continues to emphasize the role of innovation, regional and industrial policy needs to balance the necessity of protecting key nascent industries, while at the same time fostering strong competitive environments that allow both innovative and non-innovative firms to flourish. Persistent, high levels of state-protectionism, however, may disincentive firms from pursuing innovative strategies if those firms perceive that state-protectionism is the key to survival and performance.

To become a global "innovative powerhouse" by 2050, the combined results highlight the importance of institution building, coinciding along with contemporaneous efforts to reduce the role of state intervention in the market. Building a solid institutional environment reduces the high risks associated with pursuing innovation and will help facilitate the transferring of tacit knowledge leading to both intra- and inter-industrial spillovers, thereby reducing firm dependency on state protectionism, and spurring firm competitiveness. Combined with limited, strategic policy instruments and further accumulation of learning by doing, Chinese firms will better absorb learning spillovers and integrate them with in-house R&D activities. In time, it is likely that China will increase its value-added within the global production chain and contribute widely to the global stock of knowledge.

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