The Pennsylvania State University
The Graduate School

ESSAYS ON INNOVATION AND PRODUCTIVITY

A Dissertation in
Economics
by
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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2020

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Abstract

My studies focus on the determinants and aggregate implications of innovation and productivity. This dissertation includes three chapters. Chapter 1 in on the role of R&D investment in determining the relationship between finance and total factor productivity (TFP). Chapter 2 is on the quantification of the costs and benefits of R&D and patent. The last Chapter provides an analysis of the driving forces behind the patent growth in China.

Firms in developing countries are less innovative than that are in developed economies. A large body of literature has documented that the lack of financial support has hindered firms from participating in R&D investment. How much does the R&D channel account for the productivity loss caused by financial constraints? How does R&D investment affect the efficacy of self-financing in the reduction of TFP losses?

In Chapter 1, I attempt to shed light on each of these questions by using a quantitative model of R&D investment with financial frictions. In the model, R&D investment, which affects productivity evolution endogenously, is subject to financial constraints. I parameterize the model with production, innovation, and balance sheet data from manufacturing firms in China, a country with relatively less developed financial markets. Through the lens of the model, I first quantify static and dynamic TFP losses. I then analyze the transition dynamics and the steady state of the model. Finally, to gauge the importance of R&D investment for understanding the relationship between finance and TFP, I compare the results of the estimated model with a model's special case in which the productivity process is exogenous.

The estimated model implies sizeable *static* TFP losses caused by capital misallocation and *dynamic* TFP losses from distorting R&D investment. The accumulation of internal funds reduces the static TFP loss gradually. In contrast, because R&D has a persistent effect on productivity, the dynamic TFP loss rises initially

and declines later. Compared to a model with exogenous productivity, innovation investment makes firms less able to use self-financing to reduce TFP losses and prolongs the transition. Endogenous productivity growth amplifies the gains in TFP and output from financial reform, and leads to a longer-lasting consequence from a credit crunch. Improving the pledge-ability of intangible assets in China to be the US level reduces the static TFP loss only 0.4%, but the dynamic TFP loss by 7.1%.

I explore several policy implications of the quantitative model. First, I consider a financial reform that relaxes the credit constraints permanently. I find that the boosting effects of financial reform on aggregate TFP and output are amplified when considering the endogenous response of R&D investment. Second, I study a credit crunch by tightening the financial constraints for one period. I show that the detrimental impact of a credit crunch on aggregate TFP and output tends to be longer-lasting when I account for the endogenous growth of productivity. Lastly, improving the pledge-ability of intangible assets in China to be the US level reduces the static TFP loss only 0.4%, but the dynamic TFP loss by 7.1%.

Different firms undertake different levels of R&D investment. Quantifying the costs and benefits of innovation activities is essential to the understanding of firm's incentives to innovate. Innovation is a process of producing new knowledge of new products or new processes. In the process, R&D in the input while patenting is part of the output. What are the benefits of R&D from patenting and non-patenting activities?

In Chapter 2, I embed patents into the productivity evolution of a standard dynamic model of endogenous productivity change. I treat R&D as the fundamental source of endogenous productivity growth, but the marginal effect of R&D investment is affected by patenting activities. I propose a method to decompose the returns to R&D into patenting and non-patenting outcomes. The methodology also provides an evaluation of the patent value.

I apply the model to a sample of Chinese high-tech manufacturing firms. The estimated model shows: first, on average R&D investment causes around 0.45% increase (or around 0.24 million USD) in the firm value. Second, a decomposition of the return to R&D shows that non-patent innovation accounts for a majority (around 77%) of the total return to R&D. Third, the average expected value of an invention (a utility) patent is around 0.39 (0.34) million USD when measured by the increase in firm value. Lastly, the start-up costs of R&D is over ten times larger than maintenance costs. This reflects that starting a new innovation project requires a larger amount of investment than maintaining an ongoing research project. The distribution of R&D costs differs across industries.

I also perform a series of counterfactual exercises to evaluate the effectiveness of different types of R&D subsidy policies that reduce the costs of R&D investment. Some interesting results are found. First, a lump-sum subsidy is universally more effective than a marginal subsidy either in increasing the firm value or promoting innovation participation. Second, for both types of the subsidy programs, reductions in the maintenance costs cause a greater increase in the firm value. But subsidizing the start-up (maintenance) costs promotes innovation participation more under lump-sum (proportional) subsidy. Third, a lump-sum subsidy is more efficient than a proportional subsidy. In the experiment of 20% decrease in maintenance costs for R&D, the average efficiency of lump-sum subsidy is around 12 times greater than the marginal subsidy in increasing firm value, and is about twice greater in promoting the firm's innovation participation. The difference is more striking when I consider the subsidy for start-up costs of R&D.

In the past three decades, China has experienced an explosive increase in both patent applications and patent granting. Breaking the patent counts into invention patents, utility models, and designs, this extraordinary growth prevails. If different types of patents represent distinct forms of innovation, patent heterogeneity should be important for understanding the driving forces behind China's patent surge as well as its policy implications.

In Chapter 3, we study China's patent surge and its driving forces using a novel and comprehensive merged data on patent applications filed by Chinese firms. We find that R&D investment, FDI (Foreign Direct Investment), and patent subsidy have different effects on different types of patents. First, R&D investment has a positive and significant impact on patenting activities for all types of patents under different model specifications. Second, the stimulating effect of FDI on patent applications is only robust for utility model patents and design patents. Third, the patent subsidy only has a positive impact on design patents. The results imply that FDI and patent subsidy may disproportionately spur low-quality patents.

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Acknowledgments

Time flies when I look back on how it was in years go by. The journey of PhD study is more pleasant, though much tougher, than I expected when I first arrived at Penn State. At this point, I am grateful to so many people who has helped, advised, and supported me in the most challenging period of my past life.

First of all, I would like to thank my advisors: Professor Jonathan Eaton and Professor Mark Roberts. Both of them gave me invaluable guidance and support.

Professor Eaton always asked deep questions in our meetings. Many times, it took me a long time to understand his insightful comments. Though it frustrated me sometimes, it also pushed me to think deeper and finally enhanced the quality of my research. I audited his lectures on international trade three times, gaining more and more each time I stepped into his classroom. His lecturing showed wisdom and inspired me to choose academia as my career.

Professor Roberts was always supportive. His comments are usually constructive and persuasive. At the end of each meeting, he usually set the schedule for the next meeting and emphasize the things to be done. He helped me streamline my research and life. Without his advising, I can hardly graduate within five years. It is his organization and suggestions that spurred my productivity.

During my writing of Chapter 1, I benefited enormously from discussions with Professor Jingting Fan. I cannot remember how many times I went to his office to discuss with him about my project. He was approachable and offered suggestions that helped improve my paper to a great extend. I have also learnt a lot from discussions with Professor Kenneth Judd and Professor James Tybout. I am also indebted to Professor Jie Zhang, who generously shared the data with me.

Since Chaoqun quit her job and came to State College in September 2019, my life has become more colorful. I cannot express how thankful I am for her loving company. Her smiles chased away my pressure and anxiety, and shed sunshine in times of darkness.

Last but not the least, I would like to thank my grandparents who raised me up. From them, I learned to be optimistic and diligent.

Chapter 1

Finance, R&D Investment, and TFP Dynamics

1.1 Introduction

Differences in total factor productivity (TFP) are an important contributor to disparities in income and development across countries. Underdeveloped financial markets can reduce aggregate TFP by distorting innovation decisions. Despite a large literature that has documented a stimulating effect of financial development on innovation investment and productivity growth,[1] financial frictions are often absent in R&D investment models.[2] This limitation prevents us from analyzing the interplay of financial friction, R&D investment, and TFP together. The objective of this paper, thus, is to evaluate the role of R&D investment in shaping the relation between financial constraints and aggregate TFP.

R&D activities have a persistent effect on productivity. When financial constraints restrict a firm's ability to undertake R&D investment, the negative consequence on productivity will be carried over time. Endogenous R&D investment complicates the relationship between financial constraints and aggregate TFP. First, introducing R&D investment can potentially amplify the TFP loss from

[1] For the related empirical evidence, see Rajan and Zingales (1998); Chava et al. (2013); Gorodnichenko and Schnitzer (2013); Kerr and Nanda (2015), among others.

[2] See Klette and Kortum (2004); Eaton and Kortum (1999); Aw et al. (2011); Doraszelski and Jaumandreu (2013); Peters et al. (2017), among others.

financial constraints. Financial constraints, meanwhile, can cause (1) a *static* TFP loss by generating differences in the marginal product of capital across entrepreneurs– i.e., giving rise to a misallocation of capital, and (2) a *dynamic* TFP loss by constraining R&D investment and hindering productivity growth. Second, R&D investment can also influence the efficacy of self-financing in reducing TFP losses by increasing productivity and assisting the accumulation of (intangible) assets. As Moll (2014) points out, in the presence of financial constraints, the dynamism of productivity and assets is the key to understanding transition dynamics and the steady state of TFP.

How much does the R&D channel account for the productivity loss caused by financial constraints? How does R&D investment affect the efficacy of self-financing in the reduction of TFP losses? This paper attempts to shed light on each of these questions by using a quantitative model of R&D investment with financial frictions. I estimate the model using a panel of manufacturing firms in China, a country with relatively less developed financial markets. The parameterized model matches firms' size distribution as well as their decisions on R&D investment and asset accumulation. Through this model's lens, I first quantify static and dynamic TFP losses. I then analyze the transition dynamics and the steady state of the model. Finally, to gauge the importance of R&D investment for understanding the relationship between finance and TFP, I compare the results of the estimated model with a model's special case in which the productivity process is exogenous.

I find that, on average, financial constraints cause a TFP loss of 29% through the R&D channel within the sample period. This is close to the static TFP loss (37%) caused by capital misallocation. To examine the robustness of the benchmark results, I have explicitly considered the heterogeneity in R&D costs, heterogeneity in cost-benefits structure of R&D across industries, and endogenous uncertainty in R&D investment. The quantification of TFP losses is robust to all of these modifications. Re-calibrating the exogenous-productivity model predicts a similar degree of productivity loss, yet it fails to detect the dynamic TFP loss caused by distorted R&D decisions.

Over time, the accumulation of internal funds enables some firms to escape from financial constraints, which reduces TFP losses. In the model with R&D investment, the static TFP loss declines more slowly. This is because the endogenous productivity growth tends to entrap more firms in financial constraints. As a result, in the steady state, static TFP loss is reduced to be 18.4% (16.7%) in the model with endogenous (exogenous) productivity. In contrast, because of the persistent impact of R&D on productivity, the dynamic productivity loss rises initially and falls ultimately as firms become wealthier. In the steady state, dynamic TFP loss is 20%, showing only a decrease of 9%. This suggests that it is more difficult for firms to undo the dynamic TFP loss by self-financing.

I explore several policy implications of the quantitative model. First, I consider a financial reform that relaxes the credit constraints permanently. I find that the boosting effects of financial reform on aggregate TFP and output are amplified when considering the endogenous response of R&D investment. Second, I study a credit crunch by tightening the financial constraints for one period. I show that the detrimental impact of a credit crunch on aggregate TFP and output tends to be longer-lasting when I account for the endogenous growth of productivity.

My model also sheds light on the impact of using intangibles as collateral on R&D investment and TFP. In practice, products of R&D investment, such as patents and trademarks, are used as collateral when firms borrow from financial institutions.[3] In the last counterfactual experiment, I investigate the impacts of allowing more intangibles to serve as collateral on R&D investment and TFP. I find that improving the pledgeability of intangible assets in China to be the US level encourages R&D investment and reduces the static (dynamic) TFP loss by 0.4% (7.1%). Employing a policy shock on patent pledge financing in China, I also provide causal evidence supporting that increasing the pledgeability of intangible assets enhances the R&D investment in China.

This paper is closely related to studies that use quantitative models to analyze firms' incentives for undertaking R&D investment (Eaton and Kortum, 1999, 2007; Aw et al., 2011; Doraszelski and Jaumandreu, 2013; Warusawitharana, 2015; Peters et al., 2017). In these predecessor models, R&D investment entails certain costs and leads to productivity growth in the future. By assuming that firms operate

[3] As related empirical studies, Loumioti (2012) finds twenty-one percent of US-originated secured syndicated loans during 1996-2005 have been collateralized by intangibles. More recently, Hochberg et al. (2018) document that start-ups with more redeployable patents as assets are able to receive more funds from investors. And Mann (2018) shows that patents that are pledged as collateral to help US firms raise more debt and spend more on R&D.

in a perfect financial system, these models provide no room for analyzing the impact of financial development on R&D investment and productivity dynamics. Meanwhile, there is growing reduced-form evidence that financial markets do play a key role in supporting R&D investment (Rajan and Zingales, 1998; Robb and Robinson, 2012; Chava et al., 2013; Gorodnichenko and Schnitzer, 2013; Nanda and Nicholas, 2014; Kerr and Nanda, 2015; Cornaggia et al., 2015; Varela, 2018). In general, these studies employ certain indicators to measure financial development and then link them to firms' innovation behavior. The current paper contributes to these studies by explicitly considering financial constraints in a structural model of R&D investment.

This paper also contributes to the literature that focuses on the role of endogenous productivity change in understanding the impact of various distortions, particularly tax distortions (e.g., Bhattacharya et al. (2013); Bento and Restuccia (2017); Da-Rocha et al. (2017)) and financial frictions (e.g., Mestieri et al. (2017); Vereshchagina (2018); Caggese (2019)).[4] Vereshchagina (2018) and Caggese (2019) are the two most relevant papers. Vereshchagina (2018) a variation of the Bewley-Ayiagary-Hugget model (Huggett, 1993) in which firms can invest in intangible capital to improve their future productivity in a deterministic way. In contrast, this paper extends a Hopenhayn firm dynamics model (Hopenhayn, 1992) by treating productivity as a controlled Markov process: future productivity is partly random and partly under the control of R&D investment. The current paper goes on to estimate its own model by focusing on dynamic decisions about R&D and wealth accumulation. It analyzes the effect that innovation investment has on the efficacy of self-financing for reducing TFP loss along the transitional path and in the steady state.

Caggese (2019) analyzes the role of innovative investment in understanding the impact of financial constraints on firm growth. He argues that incorporating radical as well as incremental innovations can explain the differences in the evolution of firm sizes over time between poor and rich countries. My paper differs from

[4]More broadly, these studies originates from a large literature on financial frictions and economic development (see Jeong and Townsend (2007), Buera et al. (2011), Buera and Shin (2013), Midrigan and Xu (2014), and Moll (2014), among others). In most of such previous studies, the productivity process has been treated as exogenous. See also Buera et al. (2015) for an excellent review of this literature.

Caggese's work in several aspects. First, I focus on how R&D investment affects the relationship between financial constraints and productivity. Second, I allow the output of R&D investment–the intangible assets–to be used as collateral. Third, I incorporate R&D into the productivity process a lá Aw et al. (2011). Therefore, R&D investment always faces a certain degree of uncertainty in my model, as with the radical innovation modelled by Caggese (2019).

The rest of this Chapter is organized as follows: In Section 1.2, I introduce the benchmark model and a decomposition of TFP losses. In Section 1.3, then, I present the data and estimation results. Section 1.4 displays the results of the quantitative analysis, while Section 1.5 analyzes several robustness checks. Section 1.6 concludes the paper.

1.2 The Benchmark Model

In this section, I introduce a heterogeneous-firm model in which firms finance their R&D investment out of cash flow; a firm's capital investment is restricted by a collateral constraint a lá Midrigan and Xu (2014) and Moll (2014). More importantly, I also introduce intangibles as a collateral for borrowing.

1.2.1 Setup

1.2.1.1 Production

I consider an industry populated with a fixed number of firms, each producing a single variety. Firm i operating in period t uses labor l_{it}, capital k_{it}, and a constant-return-to-scale production technology to produce its output q_{it}:

$$q_{it} = \phi_{it} k_{it}^{\alpha} l_{it}^{1-\alpha} \tag{1.1}$$

where $0 < \alpha < 1$ is the capital's share. ϕ_{it} is the current state of technology. Labor is hired in a competitive market at the wage rate ω. Each firm has a constant-elasticity demand function:

$$q_{it} = p_{it}^{-\sigma}, \tag{1.2}$$

where σ is the demand elasticity and assumed to be greater than one. The revenue production function is

$$y_{it} = \left(\phi_{it} k_{it}^{\alpha} l_{it}^{1-\alpha}\right)^{\frac{\sigma-1}{\sigma}}, \tag{1.3}$$

which has decreasing returns to scale.

1.2.1.2 R&D and productivity

Following Aw, Roberts, and Xu (2011) and Doraszelski and Jaumandreu (2013), I assume that R&D affects the firm's productivity process. Specifically, letting x_{it} be R&D investment, the log-productivity follows a controlled Markov process:

$$\ln\left(\phi_{it+1}\right) = \rho \ln(\phi_{it}) + \gamma \ln(x_{it} + 1) + \xi_{it+1}, \tag{1.4}$$

where γ governs the marginal effect of R&D investment on productivity; $\gamma > 0$ means that more R&D investment leads to a more favorable productivity distribution in the future. Note that $\ln(x_{it} + 1) = 0$ when $x_{it} = 0$, meaning that zero R&D investment generates no enhancement in productivity. Also note that $\partial \ln(\phi_{it+1})/\partial x_{it} = \gamma/(x_{it}+1)$, implying that the rate of growth of firm productivity increase with x_{it} at a decreasing speed, showing no discontinuity at the extensive margin.[5] ρ is the persistence of the productivity.[6] ξ_{it+1} is an exogenous i.i.d shock that follows a normal distribution $\mathbf{N}\left(0, \sigma_{\xi}^2\right)$. σ_{ξ} measures the uncertainty facing R&D investment. A larger σ_{ξ} indicates a higher degree of uncertainty.[7]

[5] Another possible specification is $\ln(\phi_{it+1} = \rho \ln(\phi_{it}) + \gamma_0 \mathbb{I}(x_{it}) + \gamma_1 \ln(x_{it}+1) + \xi_{it+1}$, where $\mathbb{I}_{it}$ is an indicator function equals to one when x_{it} is positive and zero otherwise. Doraszelski and Jaumandreu (2013) have considered such a possibility. However, I do not find supporting evidence for this specification in our data set.

[6] Another interpretation of ρ is that it captures the depreciation of past R&D investment. To see this, note that I can rewrite this productivity process as

$$\phi_{it} = \exp\left[\sum_{s=0}^{t-1} \delta^s \gamma \ln(x_{it}+1) + \sum_{s'=1}^{t} \delta^{s'} \xi_{is'}\right],$$

which means that the state-of-art technology summarizes all of the past R&D activities and exogenous shocks.

[7] In the benchmark model, R&D investment does not alter the conditional variance of the future productivity. In an alternative specification, I relax this assumption. See more details in the section of extensions and robustness.

1.2.1.3 Financial constraints

The extent to which firms can use capital is determined by following constraint:

$$k_{it} \leq \frac{1}{1-\theta} a_{it} + \frac{\theta}{1-\theta} \phi_{it}^{\eta} \tag{1.5}$$

where $\theta \in [0, 1]$ captures the severity of borrowing constraint. A larger θ means a better financial environment where firms have better capacity to borrow. In particular, when $\theta = 1$, the capital constraint is never binding, which indicates a perfect financial system. ϕ_{it}^{η} summarizes the value of intangible assets (such as patents, trade marks, and other intellectual properties) used as collateral when a firm obtains external financing.[8] η is the elasticity between pledgeable intangible assets in response the measured productivity. A larger η means firms with relatively high productivity can borrow against more intangibles. I expect that $\eta > 0$ so that more intangible assets are available for more productive firms. Different from Midrigan and Xu (2014), who treat the intangible asset to be fixed over time, I allow it to be varying across firms and time. This more realistic setting allows us to analyze the potential effect of R&D investment on relaxing financial constraints by accumulating intangible assets.

1.2.1.4 Firm's problem and static choices

Each firm is owned by an entrepreneur whose objective is to maximize its life-time utility:

$$\mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_{it}^{1-\epsilon} - 1}{1-\epsilon},$$

where c_{it} is the entrepreneur's consumption and ϵ denotes the inverse of elasticity of inter-temporal substitution. He is subject to a budget constraint

$$c_{it} + \mathbb{I}\left(x_{it}\right) f + C\left(x_{it}\right) + a_{it+1} \leq y_{it} - wl_{it} - \left(r+\delta\right) k_{it} + \left(1+r\right) a_{it}, \tag{1.6}$$

where $\mathbb{I}\left(x_{it}\right)$ is an indicator function of x_{it} which equals one when x_{it} is positive and zero otherwise. Unlike existing R&D investment models, I assume that the

[8] In Appendix A.2, I provide a micro foundation for the chosen specification of intangible assets.

financing of R&D costs faces credit market imperfections. Hall and Lerner (2010) argue that the nature of R&D investment–intangible outcome and high degree of uncertainty, makes it more costly for innovators to use external financing for R&D activities. Consistent with their finding, I assume that R&D investment can only be financed using the firm's internal cash flow. The innovation investment is modelled as a two-step process. First, an entrepreneur needs to pay a fixed cost f to find a new research idea.[9] By introducing a fixed cost for innovation investment, the model captures an important data feature that only a small fraction of firms undertake R&D investment. The entrepreneur also needs to build research labs and hire research teams to implement the innovative idea. $C\left(x_{it}\right)$ represent these expenses. Following a large body of investment literature, I use a quadratic form for the R&D investment:

$$C\left(x_{it}\right) = \frac{d}{2} x_{it}^2. \tag{1.7}$$

Firms take the interest rate and wage rate as given, therefore I can obtain optimal choices of labor and capital by solving the following constrained optimization problem:

$$\begin{aligned} &\max_{l_{it},\, k_{it}} \left\{ y_{it} - w l_{it} - (r+\delta) k_{it} \right\} \\ &s.t.\ k_{it} \leq \frac{a_{it}}{1-\theta} + \frac{\theta}{1-\theta} \phi_{it}^{\eta} \end{aligned}$$

The first-order condition delivers that

$$l_{it} = \frac{(1-\alpha)\left(\sigma-1\right) y_{it}}{\sigma w} \tag{1.8}$$

$$k_{it} = \frac{\alpha\left(\sigma-1\right) y_{it}}{\sigma R\left(a_{it},\, \phi_{it}\right)} \tag{1.9}$$

[9] Peters et al. (2017) and Chen (2019) have documented the persistence of R&D activities and distinguished between start up costs and maintenance costs. For computational tractability, I impose that the start up costs are equal to maintenance costs.

and MRPK is given by

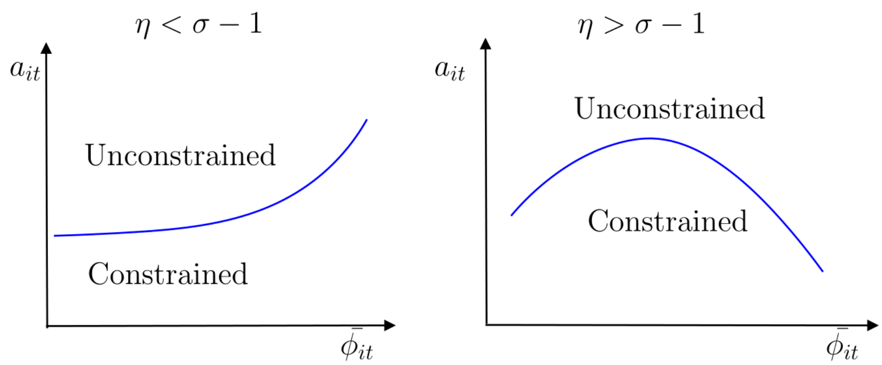
$$R_{it} = \max\left\{ r+\delta,\ \underbrace{\frac{\alpha}{\bar{m}}\left(\frac{1-\alpha}{\bar{m}w}\right)^{\frac{1-\alpha}{\bar{m}+\alpha-1}}\left[\phi_{it}\left(\frac{a_{it}}{1-\theta}+\frac{\theta\phi_{it}^{\eta}}{1-\theta}\right)^{1-\bar{m}}\right]^{\frac{1}{\bar{m}+\alpha-1}}}_{R(a_{it},\phi_{it})} \right\} \tag{1.10}$$

where $\bar{m} = \sigma/(\sigma-1)$ is the markup. There are two regimes in which MRPK are determined by different factors. When the financial constraint is not binding, $R(a_{it}, \phi_{it})$ is equal to the market's capital price $(r+\delta)$. In contrast, when the financial constraint is binding, the cost of capital $R(a_{it},\ \phi_{it})$ is jointly determined by a_{it}, ϕ_{it}, as well as parameters including θ and η. In particular, the costs of using capital is non-increasing in net worth a_{it}, meaning that wealthier firms tend to face a lower shadow costs of using capital conditional on the productivity, thus less likely to be constrained. Because the pledge-able intangible assets ϕ_{it}^{η} enter into the financial constraint, the relationship between the capital costs and productivity depends on model parameters. To see it more clearly, for any level of wealth a_{it}, let's define a cut-off productivity $\bar{\phi}(a_{it})$ as

$$R\left(a_{it},\ \bar{\phi}(a_{it})\right) = r+\delta \tag{1.11}$$

The relationship between $\bar{\phi}(a_{it})$ and a_{it} is affected by the value of η. In Figure 1.1, I illustrate how $\bar{\phi}(a_{it})$ varies with a_{it} in cases when $\eta < \sigma - 1$ and $\eta > \sigma - 1$, respectively. The left panel shows that when $\eta < \sigma - 1$, $\bar{\phi}$ is increasing with a_{it}. Given the level of net worth, firms that are more productive are more likely to have a binding financial constraint. In contrast, there is an inverted U relationship between a_{it} and $\bar{\phi}(a_{it})$ when $\eta > \sigma - 1$. In the region where $\bar{\phi}(a_{it})$ is increasing with a_{it}, the bifurcation is similar to the situation when $\eta < \sigma - 1$. However, when $\bar{\phi}(a_{it})$ is decreasing with a_{it}, conditional on net worth, less productive firms are more likely to be constrained because of a lack of intangibles to be used as collateral. In summary, if $\bar{\phi}(a_{it})$ increases (decreases) with a_{it}, it describes the highest (lowest) productivity above (below) which the financial constraints are binding. Note that when $\eta = 0$ the model degenerates into the case in which intangible assets are fixed across periods. It is also easy to see that $\bar{\phi}(a_{it})$ is always increasing in θ, meaning that relatively fewer firms are constrained in a better financial environment.[10]

Figure 1.1: Relationship between net worth and cut-off productivity for different values of η



Note: When $\bar{\phi}_{it}$ is increasing (decreasing) with a_{it}, more (less) productive firms tend to be more constrained.

1.2.2 Value functions and equilibrium

1.2.2.1 Value functions

Now I omit firm and time subscripts and formulate the entrepreneur's problem in a recursive form. The state variables are $(a,\, \phi)$. Aggregate variables are assumed to be constant and exogenous to an individual firm. An entrepreneur makes two dynamic decisions: asset accumulation and R&D investment. The firm's recursive problem is given by

$$V\left(a,\, \phi\right) = \max_{a',\, x} \left\{ \frac{c^{1-\epsilon}}{1-\epsilon} + \beta \mathbf{E} V\left(a',\, \phi'\right) \right\} \tag{1.12}$$

subject to a budget constraint:

$$c + \mathbb{I}(x) f + \frac{d}{2} x^2 + a' = \frac{1}{\sigma} y\left(a,\, \phi\right) + \left(1+r\right) a \tag{1.13}$$

[10]See the math appendix for related proofs.

where $y(a, \phi)$ is the firm's revenue generated by optimal labor and capital choices. The firm's revenue is given by

$$y(a, \phi) = \left[\frac{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}{\bar{m}w^{1-\alpha}}\right]^{\frac{1}{\bar{m}-1}} \phi^{\sigma-1} R(a, \phi)^{\alpha(1-\sigma)}, \tag{1.14}$$

The model has extensive and intensive margins of R&D investment due to the fixed cost of undertaking R&D investment. This generates kinks in the value function. Let $V^0(a, \phi)$ $(V^1(a, \phi))$ be the value function when $x = 0$ $(x > 0)$. Then $V(a, \phi)$ can be expressed as

$$V(a, \phi) = \max\left\{V^0(a, \phi), V^1(a, \phi)\right\} \tag{1.15}$$

Note that V^0 and V^1 can be written recursively as

$$V^0(a, \phi) = \max_{a'}\left\{\frac{[c(a, \phi, a')]^{1-\epsilon}}{1-\epsilon} + \beta\int_{\mathbf{R}} V(a', \phi')\, Q_0(\phi, d\phi')\right\}, \tag{1.16}$$

$$V^1(a, \phi) = \max_{a', x}\left\{\frac{[c(a, \phi, a', x)]^{1-\epsilon}}{1-\epsilon} + \beta\int_{\mathbf{R}} V(a', \phi')\, Q_x(\phi, d\phi')\right\}, \tag{1.17}$$

where the consumption levels are:

$$c(a, \phi, a') = \frac{1}{\sigma}y(a, \phi) + (1+r)a - a' \tag{1.18}$$

$$c(a, \phi, a', x) = c(a, \phi, a') - f - \frac{d}{2}x^2 \tag{1.19}$$

$Q_x(\phi, \cdot)$ $(Q_0(\phi, \cdot))$ denotes the transition kernel of the stochastic productivity process when R&D investment is positive (zero). At the extensive margin, a firm invests in R&D if and only if

$$V^1(a, \phi) > V^0(a, \phi) \tag{1.20}$$

Conditional on that the firm finds it optimal to invest in R&D, the intensive margin of R&D is characterized by (1.17). Because financial constraints lower firm's current profits, it will also have a negative effect on the firm's innovation investment. It is easy to verify that the R&D investment is non-decreasing with θ.

1.2.2.2 Equilibrium

We are interested in both the transition dynamics and steady state of our model. To this end, we consider a partial recursive equilibrium which we formally define as below.

Definition 1. A *partial recursive equilibrium* is a set of value functions $V(a,\, \phi)$, policy functions $a'(a,\, \phi)$, $x(a,\, \phi)$ such that given $P = Q = 1$:

1. $V(a,\, \phi)$ solves the firm's Bellman equation;
2. $a'(a,\, \phi)$ and $x(a,\, \phi)$ are optimal decision rules for net worth accumulation and R&D investment, respectively.

Since the partial recursive equilibrium does not require that state variables are in stationary distributions, we can analyze firm dynamics over time by simulating the model forward. To analyze the long-run effects of R&D investment in affecting the relation between finance and aggregate TFP, I also consider the steady-state equilibrium of the model.

Definition 2. A *steady-state equilibrium* is a partial recursive equilibrium such that joint distribution of (a_{it}, ϕ_{it}) is invariant over time.

Given the joint distribution of (a, ϕ), the aggregate TFP, output, and inputs are determined. In the appendix, I discuss the existence of the steady state of the model.

1.2.3 Exogenous productivity

I now briefly discuss a special case of the benchmark model with endogenous productivity: the exogenous productivity. The benchmark model degenerates into a model of exogenous productivity when we impose $\gamma = 0$ or R&D costs to be infinity. Because the benefits from R&D investment is realized through improving productivity, these conditions immediately imply that no firm would undertake R&D investment. Let $W(a, \phi)$ be the value function when no R&D investment is undertaken, I can write the firm's recursive problem as

$$W(a, \phi) = \max_{a'} \left\{ \frac{c(a, \phi, a')^{1-\epsilon}}{1-\epsilon} + \beta \int_{\mathbf{R}} W(a', \phi') Q_0(\phi, d\phi') \right\} \tag{1.21}$$

subject to the budget constraint

$$c(a,\phi,a') = \frac{1}{\sigma}y(a,\phi) + (1+r)a - a', \tag{1.22}$$

and the exogenous productivity evolution rule:

$$\ln(\phi_{it+1}) = \rho_1 \ln(\phi_{it}) + \xi^1_{it+1}. \tag{1.23}$$

When the productivity is exogenous, the only dynamic decision is asset accumulation. The equilibrium concepts I have just described for the endogenous productivity model can be readily applied here.

1.2.4 Aggregation and TFP losses

Let $\mathbb{N}$ be the set of active producers, the measure of which is N. The sectoral output is

$$Q_t = TFPQ_t K_t^{\alpha} L_t^{1-\alpha} \tag{1.24}$$

where the aggregate physical productivity $TFPQ_t$ can be expressed as[11]

$$TFPQ_t = \frac{\left[\int_{i\in\mathbb{N}} R_{it}^{\alpha(1-\sigma)} \phi_{it}^{\sigma-1} di\right]^{\frac{1}{\sigma-1}+\alpha}}{\left[\int_{i\in\mathbb{N}} R_{it}^{\alpha(1-\sigma)-1} \phi_{it}^{\sigma-1} di\right]^{\alpha}} \tag{1.25}$$

In the absence of financial constraints ($\theta = 1$), R_{it} is common to all firms and equals to $r+\delta$. This entails an efficiency allocation of capital, which implies an efficient level of aggregate TFP:

$$TFPQ_t^e = \left(\int_{i\in\mathbb{N}} \phi_{it}^{\sigma-1} di\right)^{\frac{1}{\sigma-1}} \tag{1.26}$$

R&D investment affects the evolution of productivity. By distorting R&d investment, financial constraints also have an influence on an individual firm's fundamental productivity. To analyze the TFP loss from underinvestment in R&D, I need to consider the endogenous evolution of fundamental productivity in the counterfactual scenario when $\theta = 1$.

[11] See Appendix A.1 for the derivations.

I propose a counterfactual experiment to analyze the impact of financial constraints on aggregate TFP. I choose an initial period, t_0, and treat productivity and net worth in this period as the fundamental state. The chosen fundamental state is the starting point of our analysis. Given the initial productivity ϕ_{it_0}, let's define ϕ^*_{it} as the productivity in the counterfactual scenario in which no borrowing constraint exists (see Panel A of Figure 1.2). In this case, the MRPK is equalized for all firms. The associated *best* aggregate TFP is

$$TFPQ^*_t = \left[\int_{i\in N} (\phi^*_{it})^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{1.27}$$

I can decompose the actual aggregate TFP as

$$TFPQ_t = TFPQ^*_t - (TFPQ^*_t - TFPQ^e_t) - (TFPQ^e_t - TFPQ_t)\,.$$

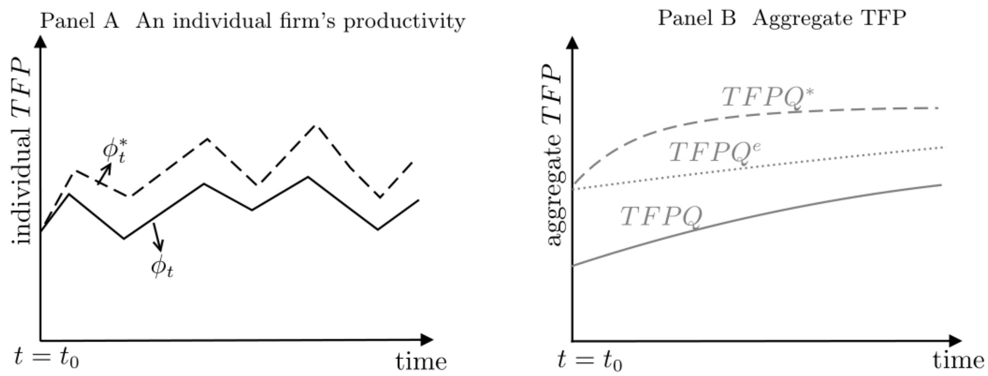
This further implies the total TFP loss as a share of $TFPQ^e_t$ can be computed as[12]

$$\begin{aligned} \textit{Total TFP Loss} =& \frac{TFPQ^*_t - TFPQ_t}{TFPQ^e_t} \\ =& \underbrace{\frac{TFPQ^*_t - TFPQ^e_t}{TFPQ^e_t}}_{\text{dynamic TFP loss}} + \underbrace{\frac{TFPQ^e_t - TFPQ_t}{TFPQ^e_t}}_{\text{static TFP loss}} \end{aligned} \tag{1.28}$$

The equation above decomposes the total productivity loss into two components (See Panel B of Figure 1.1 for three statistics of $TFPQ$). The static TFP loss is computed as in Hsieh and Klenow (2009), which measures the impact of capital misallocation in reducing the aggregate TFP. The dynamic TFP loss distortions in R&D investment caused by financial constraints. The proposed method of analyzing the TFP loss can be performed starting from any chosen states. This flexibility enables us to consider TFP dynamics and sources of its loss on the transitional path. Below I provide a characterization of these two components of TFP loss.

[12] I choose to use $TFPQ^e$ as the scaling variable to avoid the scale difference when comparing the results to that of exogenous productivity model.

Figure 1.2: Decomposition of TFP loss



1.2.4.1 Static productivity loss

The model features endogenous productivity evolution. By simulating the model, I notice that the marginal distributions of net worth and productivity are very close to log-normal distributions. I find it convenient to provide a characterization of the static TFP loss under the assumption that a_{it} and ϕ_{it} follow a joint log-normal distribution:

$$\begin{bmatrix} \log(a_{it}) \\ \log(\phi_{it}) \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} \mu_a \\ \mu_\phi \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \tilde{\rho}\sigma_a\sigma_\phi \\ \tilde{\rho}\sigma_a\sigma_\phi & \sigma_\phi^2 \end{bmatrix} \right),$$

where μ_a and μ_ϕ denote the mean of net worth and productivity, respectively. σ_a^2 and σ_ϕ^2 are the variance of net worth and productivity, separately. $\tilde{\rho}$ is the correlation between net worth and productivity. Under the assumption that productivity and MRPK are log-normally distributed, Midrigan and Xu (2014) and Ek and Wu (2018) have provided analytical expressions of aggregate TFP, showing that financial constraints reduce aggregate TFP. However, with the assumption that firms face borrowing constraints, the distributional assumption on productivity and MRPK is unlikely true because obviously MRPK is bounded below by $r + \delta$. By assuming that net worth and productivity follow a joint log-normal distribution, I provide a better approximation of the TFP loss. Employing the law of large numbers, I can express the aggregate TFP under efficient capital allocation as:

$$TFPQ_t^e = N^{\frac{1}{\sigma-1}} e^{(\sigma-1)\mu_\phi + \frac{\sigma-1}{2}\sigma_\phi^2} \tag{1.29}$$

Clearly, the efficient level of aggregate TFP is increasing with the mean and variance of the productivity distribution. For the empirical relevance, we consider $\eta < \sigma - 1$ which implies that more productive firms are more likely to be financially constrained. In this case, the fraction of constrained firms can be calculated as

$$\zeta = \int_0^\infty \int_{\bar{\phi}(a)}^\infty dG(a, \phi),$$

where $G(a, \phi)$ represent the joint log-normal distribution of (a, ϕ).[13] When ζ is relatively small, it can be shown that the aggregate TFP can be approximated as

$$TFPQ = \Upsilon_0^{\frac{1}{\sigma-1}} N^{\frac{1}{\sigma-1}} e^{(\sigma-1)\mu_\phi + \frac{\sigma-1}{2}\sigma_\phi^2} \tag{1.30}$$

where Υ_0 is defined as

$$\begin{aligned} \Upsilon_0 &\equiv \int_0^\infty \int_0^{\bar{\phi}(a)} \phi^{\sigma-1} dG(a, \phi) \\ &= \int_{-\infty}^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \Phi\left(h(z)\right) dz, \end{aligned} \tag{1.31}$$

in which $h(z) = \frac{\bar{v}(z) - \tilde{v}(z)}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}$, and

$$\begin{aligned} \bar{v}(z) &= \ln\left(\bar{\phi}(e^{\mu_a + (\sigma-1)\sigma_a\sigma_\phi + \sigma_a z})\right) \\ \tilde{v}(z) &= \mu_\phi + (\sigma-1)(1 + \tilde{\rho} - \tilde{\rho}^2)\sigma_\phi^2 + \tilde{\rho}\sigma_\phi z. \end{aligned}$$

$\Phi(\cdot)$ is the CDF of standard normal distribution. Since $\Phi\left(\frac{\bar{v}(z) - \tilde{v}(z)}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}\right) < 1$, we know that $\Upsilon_0 < 1$. This implies that $TFPQ \leq TFPQ^e$. Therefore the static TFP loss can be computed as

$$\textit{Static TFP loss} \approx 1 - \Upsilon_0^{\frac{1}{\sigma-1}} \tag{1.32}$$

It is easy to show that the static TFP loss will be increasing with μ_ϕ and decreasing with μ_a. This means that both the levels of productivity and net wealth will affect the evolution of static productivity loss. The impact of the level of productivity on static TFP loss is the key for understanding the role that R&D investment plays in altering the dynamics static TFP loss. When μ_ϕ is fixed over time, allowing firms to

[13] See the math appendix for related math derivations.

accumulate wealth will reduce the static TFP loss unambiguously. However, when a firm can invest in R&D to increase its productivity, μ_ϕ may also be growing over time, which can potentially exacerbates the capital misallocation. This implies that endogenously productivity growth may undermine the role of self-financing in reducing TFP losses over time. In addition, Υ_0 is increasing with respect to θ because a larger θ implies a higher $\bar{\phi}(a)$, meaning less firms have binding financial constraints. Lastly, it is easy to verify that the TFP loss is increasing with ζ: a larger fraction of constrained firms leads to lower aggregate TFP.

1.2.4.2 Dynamic productivity loss

Let's continue to analyze the dynamic TFP loss. Given the productivity fundamentals $\{\phi_{it_0}\}$ in period t_0, using the optimal R&D decision rule I can write down the productivity in the next period as follows:

$$\begin{aligned}
\ln(\phi_{it_0+1}) &= \rho \ln(\phi_{it_0}) + \gamma \ln(x(a_{it_0}, \phi_{it_0}; \theta) + 1) + \xi_{it_0+1} \\
\ln(\phi^*_{it_0+1}) &= \rho \ln(\phi_{it_0}) + \gamma \ln(x(a_{it_0}, \phi_{it_0}; \theta^*) + 1) + \xi_{it_0+1}
\end{aligned}$$

The difference in future productivity is determined by the gap in R&D investment, which reflects different levels of financial constraints. To control the impact of exogenous productivity shock, I impose same productivity shocks in these two scenarios. Conditional on the initial states of period t_0, the one-period mean difference of these two productivity distributions is

$$\mathbf{E}_{t_0}\left[\ln(\phi^*_{it_0+1})\right] - \mathbf{E}_{t_0}\left[\ln(\phi_{it_{0+1}})\right] = \gamma \ln\left(\frac{x(a_{it_0}, \phi_{it_0}; \theta^*) + 1}{x(a_{it_0}, \phi_{it_0}; \theta) + 1}\right) \tag{1.33}$$

If financial constraints restrict R&D investment, it is obvious that $x(a_{it_0}, \phi_{it_0}; \theta^*) > x(a_{it_0}, \phi_{it_0}; \theta)$. This implies that financial constraints cause underinvestment in R&D. Looking forward, to quantify the accumulative effects of financial constraints on TFP loss, I keep track of the two different productivity trajectories. In particular, in period $t + s$, the mean difference in productivity is

$$\mathbf{E}_{t_0}\left[\ln(\phi^*_{it_0+s})\right] - \mathbf{E}_{t_0}\left[\ln(\phi_{it_0+s})\right] = \gamma \sum_{j=1}^{s} \rho^{s-j} \ln\left(\frac{x^*_{t_0+j-1} + 1}{x_{t_0+j-1} + 1}\right) \tag{1.34}$$

where $x^*_{t_0+j-1} = x(a^*_{it_0+j-1}, \phi^*_{it_0+j-1}; \theta^*)$ and $x_{t_0+j-1} = x(a_{it_0+j-1}, \phi_{it_0+j-1}; \theta)$ represent R&D investment in two different scenarios. When productivity follows a log-normal distribution, employing (1.26), the dynamic productivity loss can be expressed as:

$$\begin{aligned} \textit{Dynamic TFP loss} &= \frac{TFPQ^*_{t_0+s}}{TFPQ^e_{t_0+s}} - 1 \\ &= \exp\left\{(\sigma - 1)\gamma \sum_{j=0}^{s} \rho^{s-j} \ln\left(\frac{x^*_{t_0+j-1} + 1}{x_{t_0+j-1} + 1}\right)\right\} - 1 \end{aligned} \tag{1.35}$$

Equation (1.35) has several implications. First, the dynamic TFP loss reflects the current and past efforts of R&D investment and piles up over time. Second, R&D investment in more distant periods tends to be less important for current productivity because of the depreciation rate ρ. These two observations are critical for the understanding of the change in dynamic TFP loss over time. As time evolves, poor firms accumulate more wealth and grow out of financial constraints. This narrows the per-period difference in R&D investment. In addition, because past disparities in R&D investment become less important, dynamic TFP loss tend to decrease eventually. Lastly, the dynamic productivity loss will also be affected by the initial state of the counterfactual experiment.

1.2.5 Empirical goals

Before I introduce the data and estimation strategy, I now lay out my empirical goals. To begin with, I am going to measure the firm-year level productivity using a rich firm-level data set. Along with the observed information on firm net worth, capital, and employees, I can parameterize the equation of capital constraint by matching the cross-section distribution of capital and labor. Then I estimate the productivity evolution equation. In particular, I follow Vereshchagina (2018) to separately estimate the endogenous productivity process with R&D and the exogenous productivity process without R&D. This helps us understand the role that R&D plays in shaping the relation between R&D and TFP. The last empirical objective is to determine the costs of R&D investment. I choose cost parameters such that the R&D investment and net worth decisions predicted by the structural model are consistent with the data.

Utilizing the parameterized model, I analyze the effects of R&D investment on the relation between financial development and aggregate TFP by varying θ. In the exogenous productivity model, the only channel through which financial development can improve aggregate efficiency is reducing misallocation. In contrast, in the endogenous productivity model R&D investment also responds to the financial development and enhances the fundamental productivity as well as aggregate TFP. The quantitative exercise allows us to quantitatively evaluate the strength of R&D channel through which financial constraints affect the productivity distribution and aggregate TFP.

Because some firms can accumulate wealth over time to overcome financial constraints, the consequence of financial frictions differs in the short- and long-run. This point is theoretically explored in Moll (2014). How does the option of R&D investment affect transition of TFP losses? Eventually, what is the impact of R&D investment on the efficacy of self-financing in cutting TFP losses? Simulations of the empirical model will help us answer these questions.

1.3 Data and Estimation

1.3.1 Data

I use the administrative income tax records from Chinese State Administration of Tax (SAT) from 2008-2011. The SAT is in charge of collecting taxes and auditing, similar to the IRS in the United States. The SAT in China maintains its own firm-level database of tax payments as well as other balance-sheet and financial statement information that is necessary for tax-relevant calculations. For the purpose of this study, I use the information to estimate productivity and calculate other relevant variables. I have obtained these tax records from 2008 to 2011. I have followed several cleaning procedures. First, I have deleted the duplicated observations within a year. For firm names that are repeated within a year, I use the tax id as their unique identifier. Second, I have deleted observations with abnormal values for interested variables. These include: (i) negative sales, debt, total asset, fixed asset; (ii) number of employees smaller than 10; (iii) birth year later than 2011 or earlier than 1900. The final data set I use for estimation is a balanced panel with 21,428 firms spanning over four years. In Appendix A.4, I have included details of data processing and the construction of relevant variables.

1.3.2 Parameterization

The estimation procedure is a two-step procedure. In the first step, I calculate productivity using the data with some externally determined parameters. Together with data on net worth, this allows us to (i) calibrate the parameters describing the financial constraints, and (ii) estimate the productivity evolution equation. The second step employs a Simulated Methods of Moments (SMM) estimator which requires solving the dynamic structural model and pin down the parameters characterizing the costs of R&D investment.

1.3.2.1 External parameterization

I first parameterize several parameters by choosing their conventional values.These parameters and their sources of values are summarized in following table.[14] The risk-free interest rate is chosen to be 0.0575, which is average of real lending interest rates between 2008 and 2011. Because the discounting rate is not separately identified in my model, I refer to the existing literature. Midrigan and Xu (2014) choose a discounting factor to be 0.92, Gopinath et al. (2017) set the discounting rate to be 0.87, and David and Venkateswaran (2019) set the value to be 0.95. In the end, I choose the discounting rate is chosen to be 0.90, which is smaller than $1/(1+r) = 0.946$.[15] The depreciation rate is set as 10% as in Song et al. (2011). I follow Midrigan and Xu (2014) to use a log-utility function. The capital share α is consistent with David and Venkateswaran (2019). Lastly, the value of the substitution elasticity is from the survey by Head and Mayer (2014).

[14]The capital share can potentially be backed out using the data if no distortions are imposed in the labor market. Note that by (1.8) I know that $\alpha = 1 - \bar{m}\omega l_{it}/y_{it}$. Therefore α can be estimated as $\hat{\alpha} = \frac{1}{NT}\sum_{n=1}^{N}\sum_{t=1}^{T}\left(1 - \frac{\bar{m}\omega l_{it}}{y_{it}}\right)$.

[15]The value of discounting rate will mainly affect the value of estimated R&D costs, it does not affect the quantitative results of analysis of aggregate TFP loss.

Table 1.1: Baseline external parameters

Parameters	r	δ	β	ϵ	α	σ
Values	0.0575	0.10	0.90	1.00	0.50	5.00

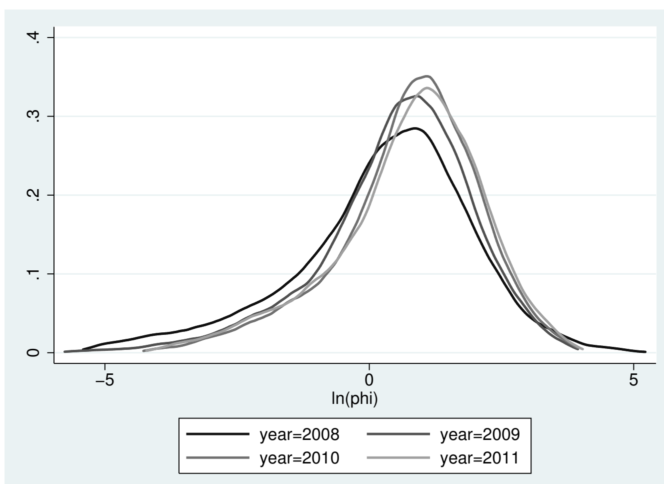
1.3.2.2 Internal estimation

Using the revenue production function (1.3), the physical productivity is estimated as:

$$\phi_{it} = \frac{(p_{it}y_{it})^{\bar{m}}}{k_{it}^{\alpha} l_{it}^{1-\alpha}} \tag{1.36}$$

I use firm's value added to measure $p_{it}y_{it}$. k_{it} is measured using the firm's deflated fixed assets. I use wage bill to measure l_{it} in order to account for the unobserved differences in human capital composition in different firms. Figure 1.3 displays the kernel density of estimated productivity. The logged productivity ranges from -5 to 5, showing a large dispersion.

Figure 1.3: Kernel density of estimated productivity



Note that θ, η, and w jointly affect the firm's choices of capital and labor. Because these choices are static, I calibrate them using the cross-section moments including averages of capital-to-net worth ratio, capital-to-productivity ratio, capital stock, and number of employees, as well as 0.25, 0.5, 0.75 percentiles of employees and capital. I choose (θ, η, w) to minimize the distance between the model-generated moments and these targeted moments. In Table 1.2, I display the value

Table 1.2: Targeted moments for internal calibration of (θ, η, w)

targeted moments	data	model
$\log(k_{it})$:		
mean	4.35	3.66
25th percentile	3.35	2.69
50th percentile	4.53	4.72
75th percentile	5.50	6.06
$\log(l_{it})$:		
mean	4.87	4.59
25th percentile	4.17	3.22
50th percentile	4.92	5.74
75th percentile	5.63	7.41
$\overline{\log(k_{it}/a_{it})}$	-0.51	-1.20
$\overline{\log(k_{it}/\phi_{it})}$	3.77	3.08

of targeted moments in the data and the calibrated model. The calibrated values for (θ, η, w) are presented in Table 1.3. $\theta = 0.324$ implies that only around 32% of the physical capital and intangible assets can be used as collateral when the firm borrows from the financial institutions. This value is smaller than that is used in the literature. One possible reason is that the intangible asset can also be used as collateral in the model. $\eta = 0.513$ implies that the one percent improvement in the productivity will lead to 0.513 percent increase in the pledge-able collateral when using external financing. Note that $\eta < \sigma - 1$, implying that the cut-off productivity function $(\bar{\phi}(a_{it}, \theta))$ is increasing in a_{it}. This predicts that wealthier firms are less likely to be constrained in the empirical model.

After obtaining the productivity estimates, I can estimate the productivity process using a regression as follows:

$$\ln(\phi_{it+1}) = \rho \ln(\phi_{it}) + \gamma \ln(x_{it} + 1) + \mu_{jt} + \xi_{it+1} \tag{1.37}$$

where μ_{jt} denotes a three-digit industry-year fixed effect. μ_{jt} captures the factors that affecting the productivity evolution while not capture by our theoretical model. I apply OLS estimator to estimate this linear model. The variance of the error term σ_ξ^2 is estimated by the sample variance of the residuals. This step gives me estimates of $\left(\rho,\, \gamma,\, \sigma_{\xi}^{2}\right)$. I present the estimation results in the three middle columns of Table 1.3. I can see that the estimated endogenous productivity process has a persistence of 0.336. R&D investment shifts up the mean of the distribution of future productivity. In particular, one percent increase in R&D investment leads to around 0.056 percent increase in the mean of future productivity. The estimate of σ_{ξ} is 1.264, indicating that there is a relatively large dispersion in the exogenous shock to productivity. I use a similar method to back out the productivity process without R&D investment. In the absence of R&D investment in the productivity evolution, the estimated productivity process has a larger persistence of 0.349. This upward bias is mainly driven by the positive correlation between R&D investment and current productivity. Now the inferred dispersion of the productivity shocks turns to be 1.274, which is greater than that inferred from the endogenous productivity process.

Table 1.3: Parameters determined using the data

Model	Calibration		OLS			SMM	
	θ	η	ρ	γ	σ_{ξ}	f	d
Endog. Prod.	0.324	0.513	0.336***	0.056***	1.264	73.21***	0.073***
			(0.006)	(0.002)		(1.684)	(0.004)
Exog. Prod.	0.324	0.513	0.349***	0	1.274	n.a.	n.a.
			(0.006)				

Note: the OLS estimation contains a full set of industry-year fixed effects. For the OLS estimation, standard errors clustered at the 3-digit sectoral level are in the parenthesis. the *** indicates significance level at 1% significance level.

Finally, I use simulated methods of moments (SMM) to estimate the parameters for R&D costs, $(f,\, d)$. I pool the data from 2008 to 2010. Given the observed net worth and productivity (a, ϕ), I solve the model to find the parameters to minimize the distance between model-generated optimal R&D investment and net worth accumulation policies and the data. Define the vector of moments for observation

i in year t as:

$$\mathbf{m}_{it}(f,d) = \begin{pmatrix} \mathbb{I}(x_{it} > 0) \\ \ln(x_{it}+1) \\ \ln(a_{it+1}) \end{pmatrix}_{\text{model}} - \begin{pmatrix} \mathbb{I}(x_{it} > 0) \\ \ln(x_{it}+1) \\ \ln(a_{it+1}) \end{pmatrix}_{\text{data}}$$

The GMM estimator for (f, d) is obtained by minimizing following objective function:

$$L(f,d) = \frac{1}{2}\left[\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{m}_{it}(f,d)\right]' \mathbf{W}(f,d)\left[\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{m}_{it}(f,d)\right] \tag{1.38}$$

where the weighting matrix is $\mathbf{W}(f,d) = \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{m}_{it}\mathbf{m}'_{it}\right]^{-1}$. For a given pair of parameters (f, d), I solve the model, simulate the optimal R&D and wealth accumulating choices, and compute the objective function. Then I find parameters that minimize the objective function.To tackle the problem of possible local maximizers, I use the Markov Chain Monte Carlo (MCMC) estimator suggested by Chernozhukov and Hong (2003).[16] The estimation results shows that the fixed cost is around 7.32 million RMB (equivalent to around 1 million USD), which is significant at 1% significance level. The fixed costs help explain that a large fraction of firms do not participate in R&D investment. The intensive margin of R&D investment is characterized by the quadratic costs. The estimate of d is 0.073 and significant at 1% significance level.

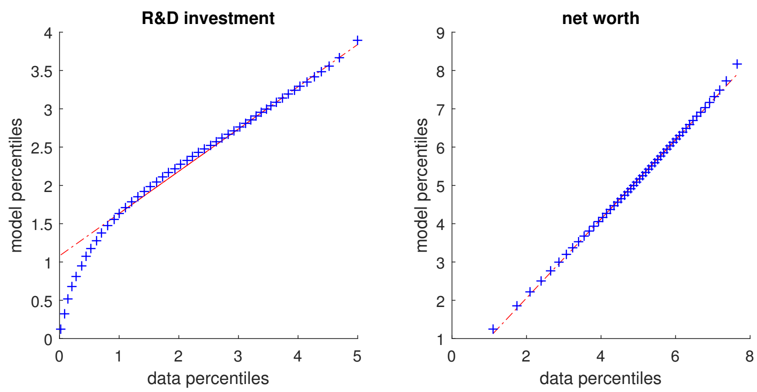
1.3.3 Model fit

The estimated model provides a good match for the observed R&D investment and net worth accumulation decisions. The estimated model predicts that 12% of firms undertake R&D investment, and the data shows that 15% of firms are active in R&D activities. In the left panel of Figure 1.4, I plot the percentiles of the simulated R&D investment distribution and future net worth distribution against those observed in the data. I can see that in either case, the fitted line is almost straight and lies along the 45-degree line, suggesting that the model simulated sample and the data sample have a similar distribution. For the R&D investment,

[16]See Appendix A.6 for a description of full computing procedures.

I see that the model matches relatively worse in terms of lower percentiles of the R&D distribution, this may suggest that R&D costs may differ across firms. A larger variable cost may be able to generate small R&D investment. Later I will discuss an extension of the model with heterogeneity in R&D costs. Looking at the right panel of Figure 1.4, I see a very tight match between the model and the data. This shows that the model is successful in predicting the decision on net worth accumulation.

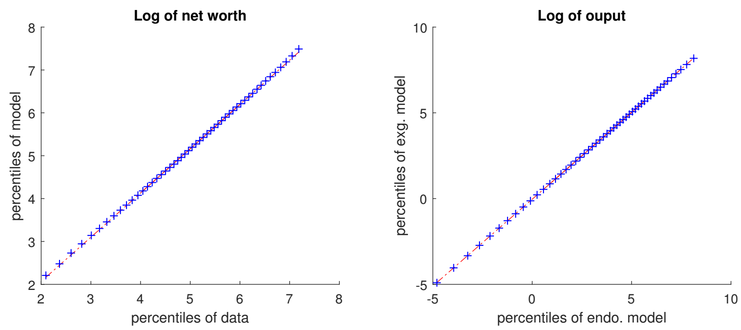
Figure 1.4: Model fit for endogenous productivity model



Note: the percentiles range from the 1^{st} percentile to 99^{th} percentile.

When comparing the results from the endogenous productivity model, it is important that these model can generate close predictions of observed outcomes. Though the exogenous model always predicts zero R&D investment, it produces very similar results of net worth accumulation rule and output. In the left panel of Figure 1.5, I plot the percentiles of model-predicted future net worth against that being observed in the data. It shows a tight match between the model and data in terms of the choice of net worth accumulation. In the right panel of Figure 1.5, I show the future output predicted by these two models are almost the same given the same states observed in the data. These results show that the exogenous productivity model and endogenous productivity model can match the net worth and output data equally well.

Figure 1.5: Model fit for exogenous productivity model



Note: the percentiles range from the 1^{st} percentile to 99^{th} percentile. The positive part of R&D investment is displayed.

1.3.4 Non-targeted moments

Now I investigate the model fit for the non-targeted moments. In particular, I explore several empirical implications from our quantitative model with R&D investment. I begin by discussing some firm-level implications of the model. These implications include cross-section correlations as well as firm-level dynamic choices. To evaluate the external validity of the model, I look at two groups of correlation moments. First, I look at the correlation between the log of MRPK ($\ln(R_{it})$) and two state variables ϕ and a. The MRPK is constructed as in Hsieh and Klenow (2009).[17] The second regression equation I am interested in is the relation between the dynamic decisions and the state variables. The closeness in the parameters between the model and the data indicates the model behaves well in terms of rationalizing the capital prices and the R&D decision. Moreover, these two regressions provides two main firm-level predictions that are testable using the firm-level data.

Implication 1 Conditional productivity, the firm's MRPK is negatively related to the firm's net worth. Conditional on firm's net worth, MRPK is negatively related to firm's productivity.

Implication 2 Conditional on productivity, both of firm's R&D investment and future net worth are positively related to firm's current net worth. Conditional on firm's net worth, R&D investment and future net worth are also positively related to firm's productivity.

[17]See Appendix A.4 for the details.

Table 1.4: Correlation between dynamic choices and state variables

Depend. var.	$\ln(R_{it})$		$\ln(1+x_{it})$		$\ln(a_{it+1})$	
	model	data	model	data	model	data
$\ln(a_{it})$	-0.318***	-0.163***	0.216***	0.219***	0.914***	0.954***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)
$\ln(\phi_{it})$	0.824***	0.648***	0.242***	0.0829***	0.294***	0.0244***
	(0.001)	(0.003)	(0.0027)	(0.0028)	(0.0018)	(0.0013)
N	85268	85268	63989	63989	63989	63989
R^2	0.818	0.705	0.309	0.119	0.966	0.911

Note: Standard errors are in parentheses; *** $p < 0.01$.

Notice that our model permits a possible negative relation between productivity and MRPK as η differs. The first implication is drawn from the static problem given the estimated parameters. Ceteris paribus, the estimated model predicts that richer producers are less likely to be financially constrained. More productive producers tend to be more financially constrained conditional on their net worth. In the second of Table 1.4, I do find such correlation patterns in the data. In the data, the partial correlation between $\ln(a_{it})$ and $\ln(R_{it})$ is -0.163, and the partial correlation between $\ln(\phi_{it})$ and $\ln(R_{it})$ is 0.648. This is close to what's being implied by the model.

Figure 1.6: Optimal choices of R&D and net worth accumulation

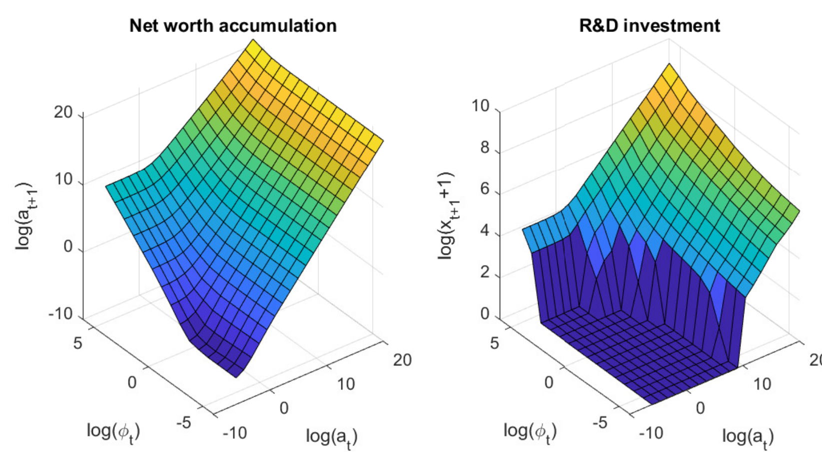


Figure 1.6 illustrates the R&D decision and net-worth accumulation decision.

The left panel depicts the optimal R&D investment. Conditional on current net worth, firms with higher productivity tend to invest in R&D investment, but less productive firms choose not to invest in R&D investment. When I fix the level of productivity, wealthier firms tend to invest more in R&D investment. Because in our model R&D can only be financed through internal cash flow,[18] the R&D investment is likely to be constrained by the available financial resources. In other words, firms are going to invest more in R&D investment as they receive more funds. Given that firms are financially constraint, increase the firm's net worth will have a positive impact on firm's R&D investment. Therefore, the model predicts a positive correlation between R&D investment and productivity as well as net worth. The right panel describes the optimal decision of wealth accumulation. Conditional on current net worth, firms of higher productivity tend to save more, anticipating that they are likely to be constrained in the future. In comparison, firms with lower productivity tend to spend more in current period. Conditional on productivity, poorer firms save more to increase its net worth in the future. The binding financial constraint increases the marginal benefits of saving, hence giving firms stronger incentives to accumulate its wealth and escape from the financial constraint.

These results are different from existing theoretical R&D models with financial constraint being absent. These model are silent about the relation between firm's wealth and R&D investment (for example, see Aw et al. (2011), Doraszelski and Jaumandreu (2013) and Eaton and Kortum (2007)). In the middle two columns of Table 1.4, I present the results for the correlation between R&D investment and state variables. The partial correlation between $\ln(a_t)$ and $\ln(1 + x_t)$ stays close to the model. This suggests that firms may face certain level of financial constraint in undertaking R&D investment.[19] Conditional on the net worth, I also see a positive partial correlation between R&D investment and productivity. This confirms that more productive firms tend to undertake more R&D investment. This mechanic relation is modelled in many R&D investment models. Note that the correlation coefficient is weaker in the data, which may suggest that the costs of

[18]In the model, the firm's cash flow includes internal profits and interest payments from holding the one-period financial asset.

[19]Another possible explanation is the cost heterogeneity, which is abstracted in our benchmark model. I have also tried to control firm fixed effects, this positive correlation remain stable.

R&D investment may be positively correlated with the productivity. Currently this is not formally modelled. In our model, productivity and wealth jointly determine the financial status of a firm, which further influences a firm's R&D decision. To some extent, the positive relation between R&D and net worth also provides indirect evidence that financial constraint matters for R&D investment.

The decision rule of future net worth accumulation is shown in the last two columns. The model predicts quite well in terms of the correlation between future net worth and current net worth. This partial correlation in the data is estimated to be 0.954, and the model predicts it to be 0.914. The correlation between future net worth and current productivity is relatively lower in the data. This may imply that there are other unobserved factors affecting the accumulation of assets.

1.4 Quantitative Analysis

In this section, I present the results of quantitative analysis based on the estimated model. Within the sample, I first show the static and dynamic TFP losses caused by financial constraints. To better understand the impact of financial constraint on productivity dynamics, I also simulate the model forward to evaluate the transition dynamics and the productivity loss in the steady state. In order to understand the role of R&D investment and endogenous productivity in determining the relation between financial constraints and TFP, I compare the results with that of the exogenous productivity model. Lastly, I perform several policy analyses based on the quantitative model.

1.4.1 Aggregate TFP losses caused by financial constraints

I set year 2008 as the initial period and treat the productivity and net worth recorded in the data as fundamentals. Using the estimated model, I simulate the model forward for 3 periods. Given the simulated state variables a_t and ϕ_t, I calculate the actual aggregate TFP based on (1.25) and the efficient aggregate productivity using (1.26) after removing the capital misallocation. A larger value of θ translates into a less tightening borrowing constraint. To investigate the impact of finance on TFP losses, I choose different values for θ and simulate the model to obtain their counterfactual $TFPQ^*$ and other interested outcomes. I then compute the static and dynamic aggregate productivity losses employing Equation (1.28).

Table 1.5: Dynamic and static TFP losses caused by financial constraint

Value of θ	TFP losses	Year			Average
		2009	2010	2011	
0.324	$Static_{ex}$	0.37	0.37	0.38	0.37
	$Static_{en}$	0.37	0.37	0.38	0.37
	Dynamic	0.22	0.31	0.35	0.29
	Total	0.59	0.68	0.72	0.66
0.5	$Static_{ex}$	0.36	0.35	0.36	0.36
	$Static_{en}$	0.36	0.36	0.36	0.36
	Dynamic	0.21	0.30	0.33	0.28
	Total	0.56	0.65	0.69	0.63
0.7	$Static_{ex}$	0.34	0.33	0.33	0.33
	$Static_{en}$	0.34	0.33	0.32	0.33
	Dynamic	0.19	0.27	0.30	0.25
	Total	0.52	0.60	0.62	0.58
0.9	$Static_{ex}$	0.28	0.26	0.26	0.27
	$Static_{en}$	0.29	0.27	0.26	0.27
	Dynamic	0.15	0.20	0.22	0.19
	Total	0.43	0.47	0.48	0.46

Note: $Static_{ex}$ and $Static_{en}$ represent the static productivity loss predicted by the exogenous productivity model and endogenous productivity model, respectively.

The results of aggregate productivity losses are reported in Table 1.5. In the estimated models, the exogenous productivity model and the endogenous productivity model predict a similar size of productivity loss from capital misallocation within the length of sample. The average productivity loss from capital misallocation is 37%. But in the model with R&D investment and endogenous productivity, the additional TFP loss from under investment in R&D is around 29%. This implies that productivity loss from the R&D channel is quantitatively important. The impact of finance on aggregate TFP will almost double as I consider the endogenous response of R&D investment. The dynamic productivity loss starts at 0.22 in year 2009 and grows to be 0.35 in year 2011. This is because the dynamic TFP loss not only reflects current R&D effort but also past R&D activities. As I increase θ, both the static productivity loss and dynamic productivity loss decreases. When $\theta = 0.9$, the total TFP loss predicted by the endogenous productivity model is 46%, with the static productivity loss being 27% and dynamic loss being 19%. In the estimated model, both the dynamic loss and static productivity loss are relatively stable when the improvement of financial institution is mild. When θ becomes larger, the decrease in TFP loss is more sensitive to the increase in θ. This is because more firms with relatively high productivity get ride of financial constraints.

Table 1.6: Aggregate implications of financial constraint: Other outcome variables

Value of θ	0.324	0.5	0.7	0.9	1.0
ζ	0.44	0.41	0.37	0.28	0.00
$\Pr(R\&D^{+})$	0.11	0.15	0.22	0.41	0.79
$\log(\overline{R\&D}^{+})$	0.34	0.42	0.66	1.05	2.92
$\log(\bar{y})$	4.59	4.79	5.07	5.64	15.96
$\log(\bar{c})$	0.87	1.01	1.27	1.92	10.06

Note: $\Pr(RD^{+})$ means the share of firms undertaking R&D investment. $\log(\overline{R\&D}^{+})$ is the log of average R&D investment for firms with positive R&D investment.

To further explore the aggregate implications of better financial institutions, I present a summary of other outcome variables in Table 1.6. To save space, I display the average values of different variables over three years. Both the static loss and dynamic loss are associated with the fraction of constrained firms. In the benchmark model, 44% of the firms are constrained. When I increase θ to be 0.9, only 28% of firms are constrained. The dynamic productivity loss is caused by the decrease in R&D investment. In the estimated model, the fraction of firms undertaking R&D investment is around 11%, while in the non-constrained model 79% of the firms choose to invest in R&D. Not only the extensive margin matters for the dynamic loss, the intensive margin of R&D investment also plays a role in affecting the productivity evolution. Focusing on the firms with positive R&D investment, I see the average R&D investment increases as I increase θ. In particular, the log of average R&D investment (for positive-R&D firms) jumps from 0.34 in the estimated model to 1.05 when $\theta = 0.9$. In the absence of financial frictions, this number in enlarged to be 2.92. Lastly, financial frictions also cause substantial losses in output and consumption.

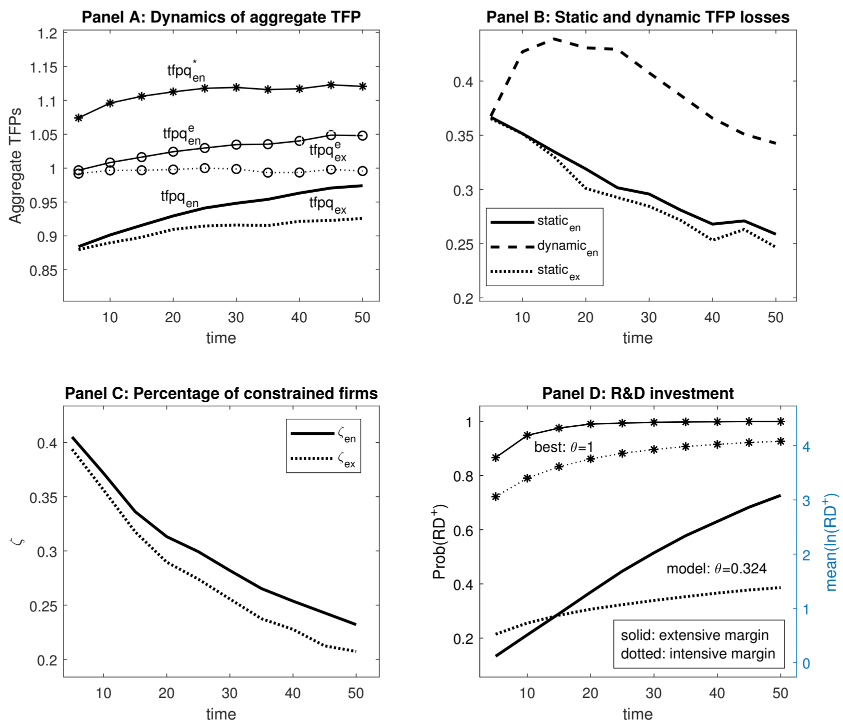
1.4.2 Transition dynamics of TFP losses

Existing studies have emphasized the importance of technology adoption in the evaluation of the impact of financial frictions on aggregate TFP (Midrigan and Xu, 2014; Restuccia and Rogerson, 2017; Vereshchagina, 2018), but much less is known about the transition dynamics of the TFP losses from the static and dynamic channels. It is interesting to see how the self-financing can undo financial constraints along the transition. Specifically, how will the incentives to perform R&D activities will alter the efficacy of self-financing? To answers these questions, I examine the impact of financial constraints on productivity dynamics and aggregate variables. Given firms' initial states observed in 2008, I simulate the model forward for 50 years and compute the interested variables.

I present the results in Figure 1.7. Panel A shows the transition dynamics of aggregate TFP. For the endogenous productivity model, I am interested three levels of aggregate efficiency: actual aggregate TFP ($tfpq_{en}$), aggregate TFP with efficient capital allocation ($tfpq^e_{en}$), and the first-best TFP ($tfpq^*_{en}$). As time evolves, $tfpq_{en}$ increases steadily with a growth rate higher than $tfpq_{ex}$. This is driven by two forces: first, a reduction in capital misallocation because of wealth accumulation. Second, the investment in R&D activities drives up the fundamental productivity. In the world where the capital constraint is absent, the fundamental productivity is also increasing over time as firm's R&D efforts continuously contribute to the productivity growth. The fundamental aggregate TFP is a key feature of endogenous productivity process. As I observe in the Panel A of Figure 1.7, the efficient productivity $tfpq^e_{ex}$ is stable over time. This implies that firm's ability of earning profits and demand of external financing are unchanged over time. As firms accumulate wealth, the actual aggregate TFP ($tfpq_{ex}$) also increases because of a lower degree of capital misallocation.

Panel B shows the transition dynamics of TFP losses. In the exogenous productivity model, the only TFP loss is the static loss caused by capital misallocation.

Figure 1.7: Transition dynamics of the financial constraint

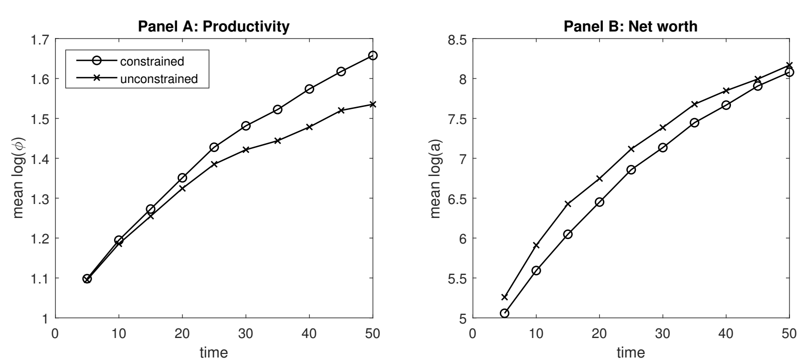


Note: Labels with 'en' represent the model with endogenous productivity, labels with 'ex' denote the model with exogenous productivity. The model simulation starts at year 2008. To focus on the transition path and the impact of initial conditions, I drop the first five years. I normalize all the aggregate TFP using the initial level of $tfpq^e_{en}$.

Over time, some firms can overcome the financial constraint through self-financing. This results in a reallocation of capital towards more productive firms and an improvement in the aggregate TFP. This mechanism is also important in explaining the pattern observed in the endogenous productivity model in which I also see a decreasing trend of TFP loss from capital misallocation. The interesting finding is that the transitional speed is slower in the endogenous model. The endogenous growth of fundamental productivity counteracts the potency of self-financing in undoing financial constraints. Two competing forces are at work. As firms become more productive, they earn more profits. This may relax the firm's financial constraints. On the other hand, more productive firms need a larger amount of external financing, which may exacerbate the financial constraint. However, the model with exogenous productivity fails to provide a framework for analyzing the dynamic interaction between financial constraints and productivity changes. The estimated model shows the second force dominates. This is supported by Panel C which shows that firms in the exogenous productivity model has a faster speed of escaping from financial constraint.

More importantly, I find a non-monotone trend of the dynamic TFP loss as time evolves. The dynamic productivity loss increases first and declines afterwards. This is mainly caused by the gap in R&D investment between the estimated model and the counterfactual case where $\theta = 1$. This is depicted in Panel D. At the beginning, the gap in R&D investment between these two scenarios is large both for the extensive margin and intensive margins. Because the difference in current productivity reflects all of the past R&D activities, the dynamic TFP loss increases as the differences in R&D investment pile up. As firms accumulate wealth, they catch up by investing more in R&D. This is especially effective at the extensive margin. As more firms are undertaking R&D investment, the loss in R&D investment shrinks. On the other hand, R&D activities in more distant history tend to be less important for current productivity due to a discounting factor. At the beginning, the dynamic TFP loss actually dominates the evolution of the total productivity loss along the transition path. As a result, the total TFP loss also increases first and then declines. This indicates that endogenous R&D investment matters for the understanding of transition dynamics of TFP losses. Because endogenous productivity growth, the ability of self-financing in easing firms' financial constraints is weaker.

Figure 1.8: Characteristics of constrained firms vs. unconstrained



As a supporting evidence for our discussion above, lastly I show the characteristics of constrained firms and unconstrained firms of the endogenous productivity model in Figure 1.8. The constrained (unconstrained) firms refer to those firms whose capital constraints are (not) binding. Panel A shows the mean of logged productivity for the constrained and unconstrained firms. Over time, relatively more productive firms are constrained, indicating that more productive firms are more difficult to get rid of the financial constraint through self-financing. On the other hand, relatively poorer firms are constrained, but the gap between the unconstrained firms and constrained firms are narrowed over time. This is mainly because firms who are more financially constrained have stronger incentives to save in order to grow out of the financial constraint. With the endogenous R&D investment, a firm compares the benefits of improving its future productivity with increasing future net worth. The trade-off between R&D investment and net worth accumulation makes it harder for the productive firms to escape from the financial constraint.

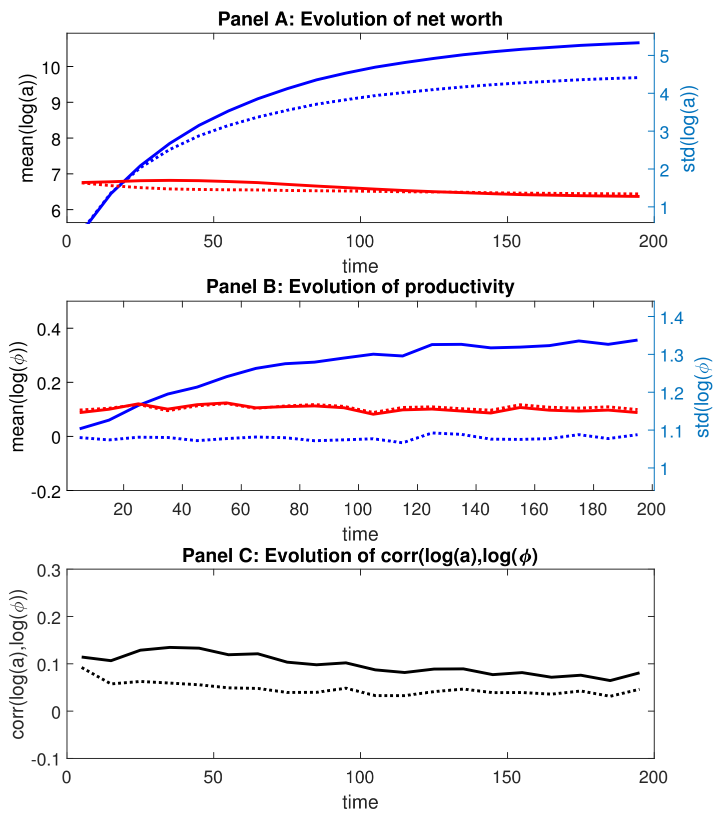
1.4.3 TFP losses in the steady state

After examining the implication of R&D investment for the transition dynamics of aggregate TFP, I now investigate how R&D investment determines aggregate outcomes in the steady state. In Figure 1.9, I show that the joint distribution of (a, ϕ) converges to a stationary distribution. With R&D investment, firms are able to improve its productivity, produce more goods, and make more profits. This in turn allows firms to accumulate more wealth. Despite the model are calibrated using the same data, the endogenous productivity model features a richer and more productive economy in the stationary equilibrium.

In Table 1.7, I show these interested indicators.[20] The first indicator I am interested is the fraction of constrained firms, denoted by ζ. Recall that in our model with static capital investment decision, ζ is also the average cash flow-investment sensitivity. With the option of R&D investment, relatively more firms are constrained. Accordingly, I observe a larger static aggregate TFP loss (18.4%) in the endogenous productivity model than in the model with exogenous productivity

[20] These variables are the averaged outcome of the last ten periods of the simulation.

Figure 1.9: Transition of state variables to the steady state



Note: In all panels, solid (dotted) lines represent the endogenous (exogenous) productivity model. For Panel A and Panel B, blue (red) lines represent the mean (standard deviation) of the interested variable.Starting for the initial period of the sample, I simulate the model for 200 periods.

(16.7%). In contrast, the aggregate TFP is much higher in the model with endogenous R&D investment. This implies that the main difference in the aggregate efficiency is driven by a difference in the fundamental productivity distribution. Most importantly, in the steady state I still see a substantial dynamic TFP loss, which accounts for 20% of the efficient aggregate TFP. In the last two columns, I present the absolute changes in aggregate TFP loss comparing to the within sample analysis. In the exogenous productivity model, the improvement in aggregate production efficiency is solely driven by a more efficient allocation of capital.

With R&D investment, there is also a substantial decrease in the static TFP loss. But the absolute change is smaller than that observed in exogenous productivity model. This is because R&D investment drives up productivity and leads to relatively more constrained firms eventually in the steady state.

I also observe a decline in dynamic TFP loss (around 9%) in the steady state compared to the initial periods of the sample. The reason is that the accumulation of net worth allows some firms to overcome the capital constraint and undertake more R&D investment. However, because of a persistent effect of R&D on a firm's productivity, the decrease in dynamic TFP loss is only .09, which is less than the half of the reduction in static TFP loss. In summary, the endogenous R&D investment affects the productivity dynamics in two ways. First, the endogenous productivity growth makes the static productivity loss more persistent over time. Second, the enduring impact of R&D investment on productivity greatly weakens the efficacy of self-financing in reducing dynamic productivity loss.

Table 1.7: Characteristics of the steady state

Indicators	ζ	$tfpq$	*TFP losses*		Δ*TFP losses*	
			Static	*Dynamic*	*Static*	*Dynamic*
Exogenous productivity	0.13	3.86	0.167	0.00	-0.21	0
Endogenous productivity	0.15	4.17	0.184	0.20	-0.19	-0.09

I conclude by connecting our findings to an insightful study by Moll (2014) on the the role of self-financing in undoing financial constraints. Using a tractable dynamic general equilibrium model in which heterogeneity entrepreneurs face collateral constraints, Moll shows that the persistence of idiosyncratic productivity shocks determines both the size of steady-state TFP losses and the speed of transitions. When shocks are persistent, steady-state TFP losses are small but transition to the steady state takes a long time. The mechanism is producers are more able to accumulate wealth through saving when the productivity shocks are more correlated over time. This provides a good benchmark in understand our results. Since R&D investment enters into the productivity process, the productivity process in our model features an endogenous persistence of productivity. The auto-correlation of productivity depends on the state variables. In particular, the persistence of productivity is $corr(\ln(\phi_{t+1}), \ln(\phi_t)) = \rho + \gamma corr(\ln(\phi_t), \ln(x_t(a_t, \phi_t))$. The endogenous component of the productivity persistence is determined by the correlation between current productivity and R&D investment. When the correlation is positive, model with endogenous R&D investment has a larger productivity persistence. Using the argument by Moll (2014), I immediately know that this will prolong the transition and reduce the static TFP loss in the steady state. In this case, how come I find a larger static TFP loss in the endogenous productivity model?

The analysis above has ignored the level effect of R&D investment. By diverting some economic resources to innovation investment, producers also enhance their fundamental productivity over time. This weakens the efficacy of self-financing along the transition as productive firms require more external financing. Even though firms can partly undo the TFP loss through self-financing along the transition, the steady-state TFP loss is larger in the endogenous productivity model because the fundamental productivity is higher. Introducing endogenous R&D investment triggers a race between the accumulation of assets and productivity growth. The TFP loss along transition and in the steady-state is determined by relative speed of wealth accumulation and productivity enhancing. Our empirical models shows that the productivity-enhancing channel wins the race and causes a large TFP loss during the transition and in the steady state.

1.4.4 Policy analysis

1.4.4.1 Financial policy

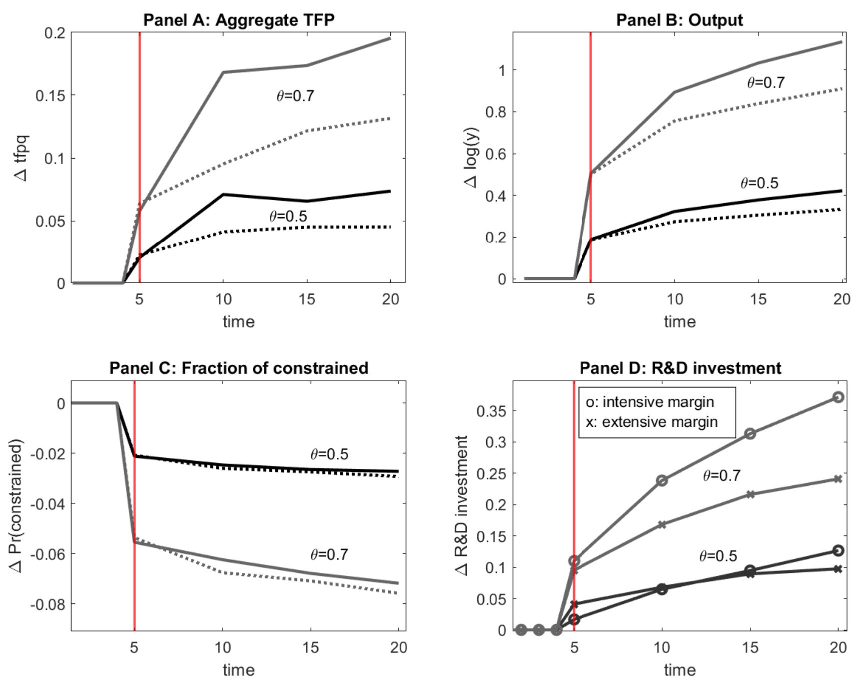
I conduct two counterfactual experiments to analyze two kinds of financial policy. First, ask how incorporating R&D investment affects the policy implication of a financial reform. I then employ the estimated model to analyze consequences of a credit crunch for both the endogenous productivity model and the exogenous productivity model.

Financial reform. A financial reform is an action that improves the efficiency of financial system permanently. I study this financial reform by enlarging θ perpetually at some time and keep track of the evolution of interested variables.[21] To

[21] A larger θ may reflect the improvement in monitoring technology which increases the cost of defaulting.

understand the role of R&D investment, I perform the same experiment for both of the endogenous productivity and exogenous productivity models. I simulate the model starting from year 2008 and introduce the financial reform at the fifth year.[22] I entertain with two values of θ: 0.5 and 0.7, indicating different levels of financial deepening.

Figure 1.10: Effects of financial reform



Note: In Panels A, B, and C, dotted lines denote the exogenous productivity model while solid lines represent the endogenous productivity model with R&D investment.

The results of this counterfactual exercise are presented in Figure 1.10. Panel A shows the response of aggregate TFP upon the initiation of financial reform. The aggregate TFP increases immediately because of the reduction in capital misallocation as more financial resources are allocated to more productive firms. In the year of starting the financial reform, the increase of $tfpq$ is almost the same for the exogenous productivity model and endogenous productivity model. No matter whether the productivity is exogenous, a deeper financial reform leads to a larger

[22]One can also introduce the policy shock at the steady state. In our case, I find qualitatively similar results. To save space, I only present the results of introducing the financial reform at non steady-state equilibrium.

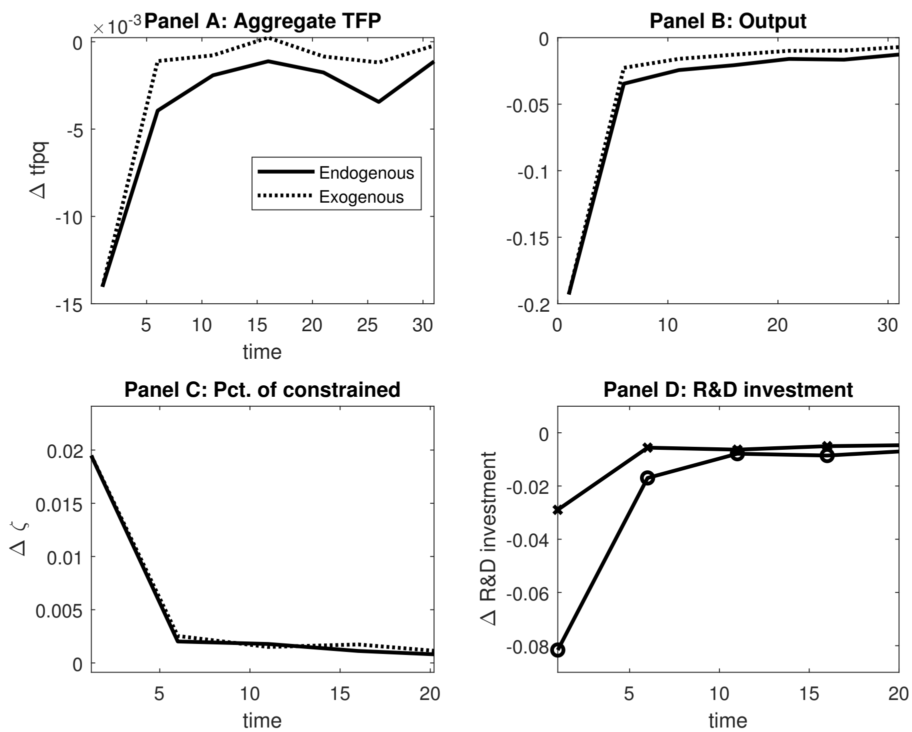
increase in the aggregate TFP. However, one year after the financial reform, with the endogenous R&D investment the aggregate TFP grows more than that of the model with exogenous productivity. This pattern persists afterwards. The change in output display a similar trend, showing that the aggregate output is co-moving with the aggregate TFP in the same direction.

The financial reform also decreases the level of financial constraint. Panel C shows the the change in ζ. Improving the financial system to be $\theta = 0.5$, the percentage of constrained firms drops about 2% (in levels) in the first year. If I change θ to be 0.7, ζ turns to be around 6% (in levels) lower in the first period. As time moves forward, the speed of decline in the exogenous productivity model is slightly slower than the endogenous productivity model with R&D investment. In the model, ζ can also be interpreted as the investment-cash flow sensitivity. Recall that the degree of capital misallocation is positively related to ζ. I can also infer that the capital misallocation decreases less in the endogenous productivity model. In Panel D, I show the change in R&D investment at both the extensive margin and intensive margins in response to the financial reform. At both margins, I see an increase in R&D investment. The increase in R&D investment shift the fundamental productivity distribution to the right and hence pushes up the aggregate TFP. This explains the gains in aggregate TFP is larger in the endogenous productivity model even though the reduction in misallocation is relatively less.

The innovation incentive amplifies the impact of the financial reform on aggregate TFP and aggregate output. Because the growth of fundamental productivity, firms need more external finance for physical capital investment. This in turn may exacerbate the firm's financial constraint. Empirically, this could be tested investigated by comparing the response of productivity and financial constraint to the financial reform for countries (or industries) with different levels of R&D intensity. For countries (or industries) that are more innovative, I expect that the productivity growth is higher while the reduction in financial constraint is lower. Due to data constraint, I do not provide formal empirical tests here. I think this is an interesting empirical question to be studied in the future.

Credit crunch. A credit crunch is a tightening of credit supply, which is reflected by a decrease in θ. When a credit crunch hits the economy, I see a decrease in

Figure 1.11: Recover from a credit crunch



Note: the shock of credit crunch is introduced in period 1.

aggregate TFP and output.[23] In the same time, relatively more firms are being constrained. In the model with R&D investment, the recover from a credit crunch is slower and the credit crunch has a long-lasting negative impact on the economy (see Panel A and Panel B in Figure 1.11). This is mainly because of the decrease of R&D investment which reduces the firm's individual productivity.[24] The effect of the plummeted R&D investment continuously lower the aggregate productivity and output. Therefore, the R&D investment not only amplifies the gains from financial reform, but also magnifies the losses from a credit crunch. Considering the response of R&D investment in the evaluation of such policies is important for evaluating the consequence of financial crisis.

[23]Experiments at the steady state generate a similar result, except that the transition back to the steady state is faster.

[24]As supporting evidence, global R&D has experienced strong decline during the financial crisis between 2008 and 2009 (OECD, 2009)

1.4.4.2 Pledgeability of intangible assets

Lastly, I investigate the impact of polices that promote the market of intellectually property rights. To separate the effect of financial reform (a larger θ) from these polices, I fix θ and focus on the counterfactual analysis of a change in η.

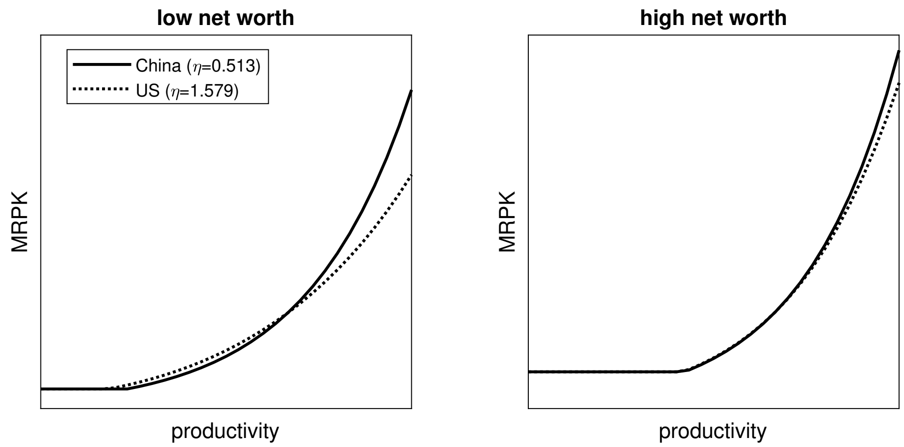
Values of η and R&D investment. In the model, R&D investment also contributes to the amount of pledged assets which helps reduce the financial constraints. It is interesting to see how the level of pledgeability of intangibles affects the firm's choice of R&D investment. A larger η implies that the pledgeable intangible assets increase dis-proportionally more for relatively more productivity firms, which, on average, makes intangible collateral more important in financing firms.[25] In the parameterized model, the ratio of intangibles to tangibles in the collateral constraint is 2.54%.[26] This number is relatively small compared to US. Loumioti (2012) finds that using intangible as collateral increases loan size by approximately 18%. This implies the value of η to be 1.579. I show the relation between $MRPK$ and productivity in Figure 1.12. In the left panel, I show the case when firms have low level of net worth. In this case, the cut-off productivity above which firms are constrained are relatively low. For these constrained firms, increasing η slightly decreases the amount of pledgeable intangible assets. This increases the shadow prices of capital, rendering these firms more likely to be financially constrained. However, as firms get more productive, a larger η means more intangible collateral is available to the firms when obtaining external financing. For richer firms that have high net worth, the cut-off productivity above which firms face financial constraint is high. As a result, a larger η leads to a lower $MRPK$ for the constrained firms. Because firms with high productivity and low net worth are easier to be financially constrained, a larger η will relieve their financial constraints relatively more.

Table 1.8 shows a comparison between China of US in terms of TFP losses and R&D participation. When we improve the collateralization of intangibles in China to be as US, both the static TFP loss and the dynamic TFP loss decrease. However, the dynamic TFP loss declines (from 29.1% to 22.0%) more than the

[25] See Appendix A.2 for the micro-foundation for the relation between η and the potential of using intangible assets as the collateral.

[26] This ratio is calculated as the average of $\theta\phi_{it}^{\eta}/a_{it}$ by pooling all firms together.

Figure 1.12: Values of η and MRPK



static TFP loss (from 37.3% to 36.9%). This is because the endogenous response of R&D investment when increasing the pledgeability of intangibles. At the extensive margin, the percentage of firms undertaking R&D investment increases from 10.6% to 19.7%. As more firms undertake R&D investment, the dynamic TFP loss decreases. The relative mild decrease in static TFP losses implies that policies aimed at increasing the usage of intangible assets as collateral may be more effective in increasing TFP through stimulating R&D investment.

Table 1.8: Relation between η and R&D investment

		TFP losses:		R&D investment:	
Country	η	*static*	*dynamic*	$Pr(R\&D^{+})$	$\log(\overline{R\&D}^{+})$
China	0.512	0.373	0.291	0.106	0.341
US	1.579	0.369	0.220	0.197	0.311

In what follows I provide reduce-form evidence supporting the counterfactual outcome. I first introduce the policy background of the intellectual property mortgage financing in China, then I present the related data and empirical results.

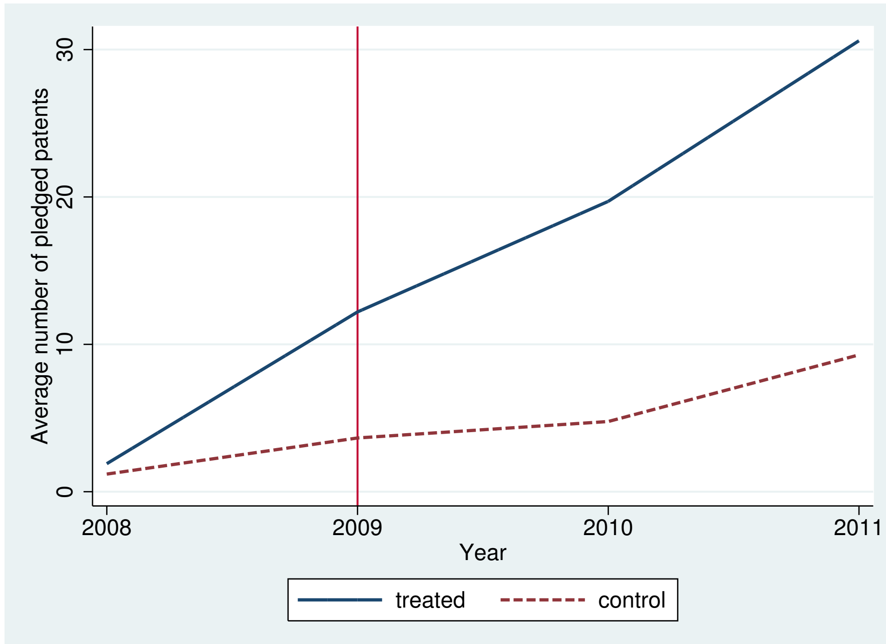
Policy background Intellectual property mortgage financing refers to an enterprise or individual using the legally owned property right of patent right, trademark right and copyright to apply for financing from banks. Using intellectual property rights as collateral is common in developed countries like United States and many European countries. For example, in 2013, 38% of US patenting firms had once pledged patents as collateral to obtain external financing (Mann, 2018). In China, partly due to the lack of protection on intellectual property rights, intellectual property mortgage financing in only at the beginning stage. In 2006, Chinese government has chosen three pilot regions (Pudong District of Shanghai, Beijing, and Wuhan) to launch the intellectual property pledge financing. After three years of trial, the State Intellectual Property Office of China (SIPO)[27] decided to promote and deepen this practice across the country. In 2009, SIPO launched two groups of pilot units for supporting intellectual property mortgage financing. The pilot units include intellectual property offices of 12 cities and/or regions. Their main task is to reduce the costs for firms using intellectual property financing. In employ this policy shock happened in 2009 to investigate the impact of pledgeability of intellectual property rights on R&D investment.

City-level data. To verify the effects of this policy, I have manually collected the contracts of pledged patents between 2008 and 2011 from the website of SIPO.[28] The records include a identifier for each patent, the date, the name of the pledger, the name of the pledgee, and the period of validity. I have identified the city of each patent holder for all of the pledged patents included in the database. This gives us information on the total number of pledged patents in different regions. In the graph below, I show the trends of average number of pledged patents for the treated cities and control cities. I can see that the average number of pledged patents for the treated cities had experienced rapid growth since 2008, climbing from close to zero to be over 30 in 2011. In contrast, the growth of the number of pledged patents in the control city is much slower, remaining to be under 10 in 2011. This graphic evidence support that these pilot regions did encourage firms to use patents as the collateral to access external financing from banks.

To investigate the impact of the increased pledgeability of intellectual properties on the R&D investment. I have constructed a dataset of city-year level R&D investment. The sample period is between 2006 and 2011 so that I am able to control for the pre-trend of R&D investment before the introduction of the policy. The R&D data are from two sources. For years of 2006 and 2007 I have acquired the R&D data from China Industrial Survey. For years between 2008 and 2011, R&D

[27]Now renamed as China National Intellectual Property Administration (CNIPA).
[28]The website address is `http://www.sipo.gov.cn/tjxx/zlqzyhtdjxgxx/`.

Figure 1.13: Number of pledged patents for treated and control groups



data are from China Innovation Survey. Note that our dataset only only contains the R&D expenditure by firms. But given that firms are the main undertaker of R&D investment, I expect that this will not overturn our empirical results.

Empirical strategy and results. To test whether introducing intellectual property mortgage financing had stimu-lated R&D investment, I adopt the Difference-In-Difference (DID) empirical strategy and specify following econometric model.

$$RD_{ct} = \beta_0 + \beta_1 time_t \times treat_c + \boldsymbol{\gamma}\mathbf{Z}'_{ct} + u_t + u_c + \varepsilon_{ct} \tag{1.39}$$

where RD_{ct} is the level of R&D investment measured in billions of RMB, $time_t$ is a dummy equal to one for years after 2009 (including 2009), $treat_c$ is a dummy indicating the treated cities. I exclude Beijing, Shanghai, Wuhan for their early exposure to a similar policy. I define cities belonging to the same province with the pilot cities as the treated cities. This allows us to capture the potential spillover and competition effects that will also increase R&D investment by firms in neighboring cities. By this classification, there are 98 cities out of 344 cities are treated cities in the full sample. $\mathbf{Z}'_{ct}$ include other city-year level control variables that may also affect the R&D performance of the city. In particular, I control for the financial development, trade openness, level of foreign direct investment, GDP, and GDP per capita. u_t and u_c represent the time and city fixed effects, respectively. ε_{ct} is the error term with mean zero.

Table 1.9: Impact of intellectual property mortgage financing on R&D investment

	Dependent variable: *R&D* expenditures			
	(1)	(2)	(3)	(4)
$time_t \times treat_c$	2.254***	0.480***	4.792***	0.642*
	(0.563)	(0.166)	(1.247)	(0.326)
$\mathbf{Z}'_{ct}$	No	Yes	No	Yes
N	1978	1127	596	371

Note: A full set of city and time fixed effects are controlled in all of the regressions. Heterosckedaticity-robust standard errors are in parentheses; *** $p < 0.01$ * $p < 0.1$.

The estimation results are reported in Table 1.9. In columns (1) and (2), I use the full sample of cities. The coefficient estimate shows that after I control for appropriate city-level factors, on average the treated cities had experienced 0.48 billion RMB additional increase in R&D investment. The result is significant at 1% significance level. I have also tried to use the sample of cities which have at least one pledged patent recorded in the database of pledged patents to form a more reasonable control group. In this case, I end up with 42 treated cities out of 100 cities. The regression results are reported in the last two columns of the table. As shown in column (4), I see that the average increase in R&D investment for the treated cities is 0.64 billion RMB and significant at 10% significance level. These results show that enhancing the pledgeability of intellectual property had stimulated the R&D investment by Chinese firms. This is consistent with the implication of the model.

1.5 Extensions and Robustness

In this section, I discuss several extensions of our model. These extensions aims to provide robustness checks to our benchmark results. The details on computation are delegated to the appendix.

1.5.1 Unobserved heterogeneity in R&D costs

In R&D investment model where the financial market is frictionless, the R&D activities are explained by the unobserved cost heterogeneity.[29] In these models, the impact of financial constraint is loaded to the R&D costs and cannot be separated from other factors. By modeling the financial constraint directly, our model explicitly provide a quantification of financial factors in affecting the firm's R&D investment. In the benchmark model, the cost function of undertaking R&D investment is common to all firms. In this case, the cost heterogeneity that affects R&D investment is attributed to the firm's financial condition. In other words, I rely on the heterogeneity in net worth and productivity to explain the R&D investment. This may lead to a bias in appraising the impact of financial constraint on R&D investment. Think of a firm which has no R&D investment. It could either be high costs of undertaking R&D or severe financial constraints that prevent them from investing in R&D.

Table 1.10: Heterogeneity in R&D costs

μ_f	σ_f	μ_d	σ_d
5.597	1.793	-2.859	3.642
(0.256)	(0.240)	(0.547)	(0.069)

Note: Standard errors are in the parenthesis.

To account for the cost heterogeneity in R&D investment, I introduce randomness to the cost function parameters. In particular, I assume f and d follow

[29] For example, see Aw et al. (2011), Peters et al. (2017), and Chen (2019).

independent joint log-normal distributions: $\ln f \sim \mathbf{N}(\mu_f, \sigma_f^2)$, $\ln d \sim \mathbf{N}(\mu_d, \sigma_d^2)$.[30] To reduce the computation burden, I discretize the normal distributions and estimate a model with 9 combinations of different values for (f, d). I then apply MCMC algorithm to obtain the estimates for R&D costs. Computational details are delegated to Appendix A.6. Table 1.10 shows the estimation results. The estimated R&D costs display certain degree of dispersion. Especially for the variable cost parameter d, the standard deviation is larger than the absolute value of its mean, implying a normal distribution with heavy tails. In Table 1.11, I display the results on productivity loss with R&D cost heterogeneity. Both of the dynamic loss and static loss are close to the benchmark model. In particular, I find a slightly larger dynamic productivity loss from distortions to R&D investment when I introduce the R&D cost heterogeneity to the model. This shows that the cost heterogeneity is unlikely to undo the productivity loss from financial constraint. On the contrary, it actually amplified the productivity loss from distortions in R&D investment decision.[31]

Table 1.11: TFP losses in model extensions

Models		*static TFP loss*	*dynamic TFP loss*
Benchmark		0.37	0.29
Heterogeneity in R&D costs		0.39	0.36
Industrial heterogeneity	high-tech	0.36	0.30
	low-tech	0.38	0.33
Endogenous uncertainty		0.37	0.30

1.5.2 Sectoral heterogeneity in innovation technology

In the baseline estimation, I impose a common cost-benefits structure of the R&D investment for all the industries. However, the participation in R&D activities differ across industries. It is documented that different industries may have different costs and benefits of innovation (Peters, Roberts, and Vuong, 2016). To examine

[30] I also considered including a correlation coefficient. The estimation results shows the correlation is close to zero and not statistically significant.

[31] Separating the impact of heterogeneity in the fundamental R&D costs and financial constraint will be important for the future work on quantifying the impact of financial constraint on innovation and TFP.

the impact of heterogeneity, I classify the industries into high-tech and low-tech industries based on the *2002 Catalogue of High-tech Industry Statistics* developed by the China National Bureau of Statistics.[32] According to this classification, in the sample 56 out of 639 four-digit industries are high-tech. High-tech firms perform better in participating R&D investment. In the dataset, 43.4% of high-tech firms engage in R&D activities while 16.8% of non-high-tech firms undertake R&D investment. The R&D intensity (R&D-to-sales ratio) also differs between the high-tech industry and the low-tech industry. The low-tech industry has an R&D intensity of 0.5% while the high-tech industry 1.8%. I can expect that the participation in R&D activities is an outcome of differences in costs and benefits of R&D investment.

1.5.2.1 Estimation by high-tech and low-tech industries

To understand the importance of industrial heterogeneity in affecting the results of our quantitative analysis, I estimate the empirical model by high-tech and low-tech industries. First, I estimated the productivity evolution equation separately for high-tech and low-tech industries. The estimation results are reported in Table A.2. All of the coefficients estimates are significant at 1% significance level. The productivity do differ across this two groups of industries. The productivity is more persistent in the high-tech industry while the productivity-R&D elasticity is slightly lower in the high-tech industry. Moreover, the dispersion of the productivity shocks is larger in the high-tech industry. I continue to undertake the structural estimation based on the estimated productivity process. The structural estimation process is the same except that now I separately estimate the R&D costs for high-tech and low-tech industries. The estimation results are shown in Table 1.12. I find smaller fixed costs and marginal costs for R&D investment in

[32]The catalogue mainly refers to the methods adopted by the Organization for International Economic Cooperation and Development (OECD), and adopts relatively high standards according to the R&D intensity of manufacturing industry and the actual status of development of China's industry. In the 2002 Catalogue, high-tech industries are divided into 8 major sectors, covering 59 manufacturing industries and 2 software services.The eight major areas are: nuclear fuel processing, information chemical manufacturing, pharmaceutical manufacturing, aerospace manufacturing, electronics and communication equipment manufacturing, electronic computer and office equipment manufacturing, medical equipment and instrumentation manufacturing, and public software services.

the high-tech industries than in low-tech industries. This suggests that innovative ideas are easier to find and implement in the high-tech industries compared to the low-tech industries. In the high-tech industry, the financial constraint causes a dynamic productivity loss around 0.30 and a static productivity loss around 0.36, which is very close to the benchmark results. In the low-tech industry, the productivity losses are slightly higher. This result is mainly driven by the relatively higher productivity-R&D elasticity in the low-tech sectors. Again, these results confirms the robustness of our benchmark results.

Table 1.12: R&D costs parameters for high- and low-tech sectors

Sectors	Productivity evolution			R&D costs	
	ρ	γ	σ_ϵ	f	d
High-Tech	0.384	0.0513	1.289	70.14	0.031
Low-Tech	0.332	0.0564	1.273	113.49	0.135

I am also interested in the long-run dynamics of productivity loss. To this end, I also simulate the model to see the transition dynamics of the share of dynamic productivity loss in total productivity loss. Both for high-tech industries and low-tech industries, I see a declining trend for the importance of dynamic productivity loss caused by under investment in R&D. This reflects that the static loss caused by capital misallocation is declines slower as the wealth accumulates. This is also consistent with our benchmark quantitative results. This shows that our analysis is robust to considering industrial heterogeneity in R&D costs and benefits.

1.5.3 Innovation with endogenous uncertainty

Now I examine the robustness of our results when subject to a different innovation technology. In our benchmark specification, the future productivity is only subject to exogenous productivity shocks. But innovation is full of uncertainties and risks. To capture the impact of uncertainties underlying in the innovation process, I extend the formulation of the productivity process specified by Warusawitharana (2015). The productivity improvement is assumed to be step-by-step. Let $\kappa_{it} \in \{0, 1\}$ be the random variable representing the innovation outcome, with $\kappa_{it} = 1$

meaning the innovation outcome is successful. κ_{it} follows a binomial distribution with probability of success equal to

$$\Pr\left(\kappa_{it}=1|x_{it}\right)=1-\exp\left(-\psi x_{it}^{\vartheta}\right) \tag{1.40}$$

where ψ is the parameter governing the overall efficiency of R&D investment in increasing the probability of success, ϑ capturing the curvature of this innovation function. The productivity evolution equation is specified as

$$\ln\phi_{it+1}=\rho\ln\phi_{it}+h\kappa_{it}+\mu_{jt}+\xi_{it+1} \tag{1.41}$$

where $\xi_{it+1}\sim\mathbf{N}\left(0,\,\sigma_{\xi}^{2}\right)$ and μ_{jt} is the industry-year fixed effects. In addition to the exogenous productivity shocks, the uncertainty in the innovation outcome is captured by the randomness in κ_{it}. I employ the probability density function of ϕ_{it+1} and apply the Maximum Likelihood Estimator (MLE) to obtain estimates for the associated parameters. Employing these the estimated productivity process, I then conduct the structural estimation to obtain the R&D costs parameters using the same structure of R&D costs. Notice that under this productivity process, I do not require a large fixed cost to capture the extensive margin of R&D investment. Even the coefficient of the variable R&D costs is much smaller. This is because the productivity process with endogenous uncertainty generates lower returns to R&D investment. As I show in Appendix A.5, this cost-benefits structure for R&D investment entails a negative relation between R&D investment and productivity, which is not consistent with the data.

Table 1.13: Parameters for innovation with endogenous uncertainty

Productivity process					R&D costs	
ρ	σ_ξ	ψ	ϑ	h	f_1	d_1
0.335	1.262	0.076	1.080	0.573	$1.9e^{-8}$	$1.7e^{-5}$

Nevertheless, the quantitative results show a similar result for the importance of dynamic productivity losses. In the last row of Table 1.11, I see that the productivity loss is quite similar to that in the benchmark model. This shows that the results is robust to alternative modelling of R&D investment.

1.6 Conclusion

This paper studies a dynamic R&D investment model with financial frictions to help understand the role of innovation in shaping the link between finance and aggregate TFP dynamics. A parameterized model consistent with important aspects of firm-level decisions on R&D investment and net worth accumulation shows a sizeable TFP loss caused by distortions of R&D investment and capital misallocation. As time evolves, self-financing does enable some firms to grow out of their financial constraints. However, productivity-enhancing innovation investment undermines the efficacy of self-financing in reducing TFP loss. Dynamic TFP loss is more persistent than the static TFP loss. More interestingly, the dynamic TFP loss amplifies in the beginning as the effect of R&D investment on productivity persists over time. In the long run, the TFP loss generated by distortions of R&D investment is mainly caused by the intensive margin of R&D investment itself. These results show that R&D investment not only affects the size of TFP losses due to financial constraints, but it also affects the transition dynamics of aggregate TFP.

Further counterfactual analysis then shows that innovation investment amplifies the TFP gains from financial reform and causes a more longer-lasting consequence in terms of a credit crunch. This finding implies that the benefits of financial reform may be severely under-evaluated if we ignore R&D investment. The counterfactual with respect to the pledgeability of intangible assets in obtaining loans shows that improving the tangibility of collateral may be an effective measure in reducing dynamic TFP loss but has limited impact on static TFP loss; developing countries can increase TFP by establishing a better market of intellectually property rights.

Because I do not have data on intangible assets, I choose a parsimonious way of modeling the relationship between pledgeable intangible assets and productivity. The accumulation of intangibles, though, is an important channel through which R&D investment helps firms to relieve their financial constraints. Unveiling the function that intangible assets play in reducing firms' financial constraints would be an interesting avenue of future study.

Chapter 2

A Cost-benefit Analysis of R&D and Patents: Firm-level Evidence from China

2.1 Introduction

Innovation is a key engine of productivity growth. Quantifying the costs and benefits of innovation activities is essential to the understanding of firm's incentives to innovate. Innovation as a process of producing knowledge: R&D is the input while patenting is part of the output, which ultimately affects firm productivity. The interplay among R&D investment, patents, and productivity is formally analyzed in the econometric models linking innovation outcome to R&D investment, and allowing the productivity to be affected by the innovation output (Crépon et al., 1998; Mairesse et al., 2005; Raymond et al., 2015). In these models, all of returns to R&D is captured by the innovation output which are usually measured by patents. However, since only part of the invention is patentable, these studies may obtain a biased estimate for returns to either R&D or patents. Moreover, only including R&D investment in the productivity process gives no room for analyzing the structure of R&D benefits.

Instead of viewing patents as the only innovation output, this study admits patents as a part of innovation outcome and allows for non-patent inventions to affect the firm's future productivity. In particular, I treat R&D as the fundamental source of endogenous productivity growth, but the marginal effect of R&D investment is affected by patent outcomes. Therefore, my specification is an extension of the productivity process considered in the innovation and productivity literature.[1] This seemingly small change has ramifications in understanding the structure of returns to R&D investment.

Building on the knowledge capital investment model by Hall and Hayashi (1989) and Klette (1996), the endogenous productivity approach models the uncertainty facing the R&D investment by introducing R&D investment into the productivity process(Aw et al., 2011; Doraszelski and Jaumandreu, 2013; Peters et al., 2017). In particular, the firm's productivity is modeled as a controlled Markov process. Current R&D investment shifts the conditional mean of the future productivity. By loading the impact of distant past R&D expenditures in current productivity, this approach avoids the problem of calculating the knowledge stock for each firm. With the exogenous shocks, this framework allows for different productivity levels even for firms with identical historical path of R&D expenditures. Recently, Peters et al. (2017) (PRVF hereafter) explicitly consider the uncertainty to the innovation process and assume that only the realized innovation affects future productivity. Note that a large part of the innovation output is the accumulation of tacit knowledge that are difficult to measure. In this case, the stochastic error term in the productivity process will contain the information of R&D investment that is positively correlated with the variables of innovation output. This endogeneity issue causes a bias to the estimates of returns to R&D. This paper proposes a method of dealing with this problem by allowing both the R&D investment and innovation output enters the productivity process.

I follow the main setup of the framework in PRVF, but have introduced two main changes: (1) instead of focusing on directly measured innovation outcome, I use patent counts as an important indicator for innovation outcomes; (2) I let productivity be dependent on R&D even after conditioning on patents. By doing these, I am able to provide a decomposition of returns to R&D investment into components related to patents and non-patents. This leads to an estimator of

[1] See Hall and Lerner (2010) and references therein for the productivity specifications used in estimating returns to R&D.

the private benefits of patents based on the marginal increase in the firm value caused by patents. Different from Pakes (1986) in which the value of holding a patent is determined by solving an optimal stopping problem, this study measures the expected value of a patent while treating patent applications as a stochastic outcome of R&D investment. This approach can be applied to any data sets with information on R&D, patents, and production activities.

I take the model to a sample of Chinese high-tech manufacturing firms. The main findings from the structural estimates are as follows. First, on average R&D investment causes around 0.45% increase (or around 0.24 million USD) in the firm value. Note that this value much lower than the estimates obtained by PRVF, who find that R&D investment increases firm value by 6.7 percent and 4.413 million Euros for the median high-tech firm in a sample of German firms. Second, a decomposition of the return to R&D shows that non-patenting innovation accounts for a majority (around 77%) of the total return to R&D. Third, the average expected value of an invention (a utility) patent is around 0.39 (0.34) million USD when measured by the increase in firm value. Lastly, the start-up costs of R&D is over ten times larger than maintenance costs. This reflects that starting a new innovation project requires a larger amount of investment than maintaining an ongoing research project. The R&D costs distribution differs substantially across different industries.

Using the estimated model, I perform a series of counterfactual exercises to evaluate the effectiveness of different types of R&D subsidy policies that reduce the costs of R&D investment. Some interesting results are found. First, given the model specification, lump-sum subsidy is universally more effective than marginal subsidy either in increasing the firm value or promoting the innovation participation. Second, for both types of the subsidy programs, reductions in the maintenance costs cause a greater increase in the firm value. But subsidizing the start-up (maintenance) costs promotes innovation participation more under lump-sum (proportional) subsidy. Third, lump-sum subsidy is more efficient than proportional subsidy. In the experiment of 20% decrease in maintenance costs for R&D, the average efficiency of lump-sum subsidy is around 12 times greater than the marginal subsidy in increasing firm value, and is about twice greater in promoting the firm's innovation participation. The difference is more striking when I consider the subsidy for start-up costs of R&D.

This study is closely related to literature on quantifying returns to R&D. The knowledge capital model of Griliches (1979) has been a corner stone of this literature. In this framework, the investment in innovation by the firm creates knowledge stock, which is similar to physical capital in the way that they enter into the production function. The most important extension related to this paper is the econometric framework proposed by Crépon, Duguet, and Mairesse (1998) (CDM hereafter) which estimates a reduced-form model incorporates R&D, patents, and productivity. Recently, Raymond, Mairesse, Mohnen, and Palm (2015) have extended this framework to a dynamic setting. However, the knowledge-stock approach faces the problem of estimating the firm's knowledge stock. It also rules out the high degree of intrinsic uncertainty facing innovation investment.

This study contributes to the existing literature in several aspects. First, it enriches the literature on quantifying returns to R&D by providing a decomposition of the benefits of R&D into patenting and non-patenting channels. The empirical finding suggests that non-patenting R&D investment plays a major role in returns to R&D. Second, I provide a new method of quantifying the private value of patents. Third, the empirical implementation in this paper provides a first structural analysis on the costs-benefits structure of R&D and patents in China, thus contributing to the literature on understanding the innovation activities in China.[2] The estimation results show that non-patents innovation accounts for most of returns to R&D. Moreover, the relative small benefits of R&D activities and relatively high start-up R&D costs help explain low participation in investing R&D.

The rest of this paper is organized as follows. In Section 2, I outline the R&D model and methodology for estimating the benefits of R&D and patent value. Data are introduced in Section 3. Section 4 provides the empirical results. Section 5 is the counterfactual analysis on the effectiveness of R&D subsidies. Section 6 concludes the paper.

[2]See, for example, Hu and Jefferson (2009), Hu et al. (2017), and Chen et al. (2017).

2.2 The Empirical Framework

In this section, I first briefly lay out a standard model of dynamic model with R&D investment and patents. The basic structure of the model is similar to that considered in Aw et al. (2011); Doraszelski and Jaumandreu (2013); Peters et al. (2016, 2017). In particular, compared to Peters et al. (2017), I allow that both R&D and patents play a role in shifting the distribution of future productivity. Then I provide a decomposition of returns to R&D as well as a quantification of the patent value.

2.2.1 Model

In PRVF, a firm's R&D decision changes the probability of realizing product or process innovations, which affect the firm's future productivity and expected profits. In their specification, only the innovation outcome (process or product innovation) caused by R&D activities has an impact on the firm's future productivity and hence future profits. In contrast, I allow both R&D and patents enter the productivity evolution equation while the creation of new ideas represented by observed patent applications affect the marginal effect of R&D on future productivity.

This model comprises of four parts. The first part is the firm's patents production function that links the distribution of patents with R&D investment by the firm. The second component is the cost function of investment in R&D, which is influenced by the previous experience in R&D. The third component of the model links a firm's patent activities with the process of productivity evolution, in which patents and R&D alter the probability distribution of the firm's future productivity. The last component of the model expresses the profits as a function of current R&D activities and future productivity. In equilibrium, each firm chooses the optimal level of investment in R&D to maximize its expected profits.[3]

R&D-patents linkage. A firm can affect the output of patents and further affect the evolution of productivity and profits through participating in R&D activities. We define two binary variables n_{it} and b_{it} , where n_{it}, $b_{it} \in \{0, 1\}$ to capture this information for invention patents and utility patents, respectively. $n_{it} = 1$ ($b_{it} = 1$)

[3]As I show in the appendix, this framework can easily be extended to accommodate intensive adjustment of R&D investment.

if firm i produces invention (utility) patents in year t. The linkage between R&D and patents is modeled as a cumulative joint distribution of invention patents and utility patents conditional on the past decision on R&D, $P(n_{it+1}, b_{it+1}|rd_{it})$.

By formulating the R&D-patent linkage as a conditional joint cumulative distribution function, we implicitly take the correlation between invention patents and utility patents into consideration. This can be caused by the idea diffusion within the firm. We also expect that firms engaging in R&D activities are more likely to produce invention or utility patents. Lastly, we do not model the possibility that different firms have different inclination to protect their ideas by creating patents. However, by selecting high-tech industries, we try to alleviate the concern that some firms may not want to protect their innovation via patenting because high-tech firms are more willing to file patent applications when they create new ideas. In addition, our sample period starts from 2002, before which China has implemented several amendments to patents law aimed to strength the protection of intellectual property rights (Hu and Jefferson, 2009). As a result, our measure is an average of the industry-specific propensity of submitting patent applications.

Firm's revenue and profits. The demand is CES with elasticity of σ. The log of firm's short-run revenue from selling products is given by:

$$r_{it} = (\sigma - 1)(\beta_k k_{it} + \beta_a a_{it} + \phi_{it}) + \mu_0 + \mu_t \tag{2.1}$$

where k_{it} is the log of the firm's capital stock, and a_{it} is the firm age.[4] μ_0 is a constant term. μ_t is a year-specific variable common to all firms; μ_t contains information on factor prices. k_{it} is treated as a fixed factor in the short-run. ϕ_{it} represents the revenue productivity, which includes firm's production efficiency as well as the idiosyncratic demand shifter. The firm's short-run profits is:

$$\pi_{it} = \frac{1}{\sigma}\exp(r_{it}) \tag{2.2}$$

Productivity evolution. I modify the process of productivity evolution in PRVF and assume that both past R&D activity and current patenting activities affect future productivity. Specifically, the distribution of future productivity is affected by a firm's past productivity (ϕ_{it}) and R&D activities (rd_{it}) and logs of the current

[4]See Appendix B.1.1 for a detailed derivation.

realizations of invention patents (n_{it+1}) and utility patents (b_{it+1}). As an extension to existing literature, I allow both R&D activity and patent activities enter into the productivity evolution equation. In my specification, the effect of R&D investment on future productivity depends on the patents.Specifically, the evolution equation of firm productivity is as following:

$$\phi_{it+1} = h(\phi_{it}, rd_{it}, rd_{it} \times n_{it+1}, rd_{it} \times b_{it+1}) + \varepsilon_{it+1}, \tag{2.3}$$

where $h(\phi_{it}, rd_{it}, rd_{it} \times n_{it+1}, rd_{it} \times b_{it+1})$ is the conditional mean of future productivity and ε_{it+1} is an i.i.d stochastic shock normally distributed with zero mean and variance σ_ϵ^2. This formulation assumes that (1) a firm's productivity is persistent over time, implying that future productivity will be affected by its current productivity; (2) R&D and patent counts jointly shift the mean of future productivity, with R&D being the fundamental source of endogenous productivity change; and (3) productivity change is affected by stochastic shocks ε_{it+1}. More importantly, I allow the impact of R&D on the future productivity depends on the outcome of patents. To account for the difference between invention patents and utility patents in affecting the firm's future productivity, we may allow that $\partial h/\partial n_{it+1}$ and $\partial h(\phi_{it+1})/\partial n_{it+1}$ to be different. It is worth noting that the formulation of productivity process is different from that considered in PRVF. In the specification of PRVF, only the innovation outcomes enter into the productivity evolution process.

R&D costs and equilibrium. Following PRVF, the innovation cost is assumed to be dependent on prior R&D experience and current capital stock. For firm i in year t, its innovation cost C_{it} is given as:

$$C_{it} \sim \exp(\kappa_m \times rd_{it-1} \times k_{it} + \kappa_s \times (1 - rd_{it-1}) \times k_{it}), \tag{2.4}$$

where $\exp(\cdot)$ represents the exponential distribution. Hence the cost of investing in R&D follows an exponential distribution with a mean of $\kappa_m k_{it}$ when $rd_{it-1} = 1$, and with a mean of $\kappa_s k_{it}$ when $rd_{it-1} = 0$. κ_m and κ_s can be different, implying that the distribution of maintenance costs differs from start-up costs. k_{it} enters the distribution of R&D costs because of the scale effect that a firm with larger capital stock are required to hire more researchers and build larger research labs;

k_{it} will be treated as exogenous. The state variables are $s_{it} = (\phi_{it}, rd_{it-1})$. The firm's decision on R&D will affect the evolution of *sit*. The firm's value function $V(s_{it})$ can be calculated as:

$$V(s_{it}) = \pi(\phi_{it}) + \\ \beta \int_0^{\infty} \max_{rd_{it}} \{\mathbf{E}_t V(s_{it+1}|\phi_{it}, rd_{it} = 1) - C_{it}, \mathbf{E}_t V(s_{it+1}|\phi_{it}, rd_{it} = 0)\} \, dG(C_{it}) \tag{2.5}$$

where β is the discount factor. $G(c) = 1 - \exp(-C_{it}/\gamma_{it})$ for $c \geq 0$ and zero otherwise. The expected future value of the firm is an expectation over the future productivity levels and counts of patent applications:

$$\mathbf{E}_t V(s_{it+1}|s_{it}) = \sum_{n_{it+1}} \sum_{b_{it+1}} \int_{\phi}^{\prime} V(s_{it+1}) dF(\phi'|\phi_{it}, n_{it+1}, b_{it+1}, rd_{it}) P(n_{it+1}, b_{it+1}|rd_{it}) \tag{2.6}$$

Note that 2.6 is composed of two parts representing two kinds of uncertainties facing innovation. The first uncertainty comes from the creating of applicable patents (or creating new ideas); the second uncertainty comes from the response of future productivity to the future patenting activities and R&D decision in the previous year. The firm maximized its firm value, which implies that a firm will choose to invest in RD if and only if

$$\Delta EV(\phi_{it}) \equiv \mathbf{E}_t V(s_{it+1}|\phi_{it}, rd_{it} = 1) - \mathbf{E}_t V(s_{it+1}|\phi_{it}, rd_{it} = 0) \geq C_{it} \tag{2.7}$$

In equilibrium, a firm will only invest in R&D as long as the expected net benefit from R&D is greater than the costs.

2.2.2 R&D benefits decomposition and patent value

R&D benefits decomposition. Given the structure of the model, I decompose the benefits of R&D into components related to patent counts. One novelty of the current paper is that I provide an analysis of returns to R&D through patent and non-patent channels. Following PRVF, the long-run benefits of R&D is measured as the relative change in the expected firm value caused by R&D investment:

$$LB(\phi_{it}) = \frac{\mathbf{E}V(s_{it+1}|\phi_{it}, rd_{it} = 1) - \mathbf{E}V(s_{it+1}|\phi_{it}, rd_{it} = 0)}{\mathbf{E}V(s_{it+1}|\phi_{it}, rd_{it} = 0)} \tag{2.8}$$

Note that conditioning on that a firm is undertaking R&D investment, its firm value is calculated as a weighted average of different states of realization of patents (n_{it+1}, b_{it+1}). In case when the patent count is zero and the firm is active in R&D investment, that is $(n_{it+1}, b_{it+1}, rd_{it}) = (0, 0, 1)$, the non-patent channel through which R&D benefits is realized can be computed as:

$$LB_N(\phi_{it}) = P(0, 0|1) \int_{\phi'} V(s_{it+1}) dF(\phi'|\phi_{it}, 0, 0, 1), \tag{2.9}$$

Similarly, the R&D benefits realized through the patent channel is:

$$LB_P(\phi_{it}) = \sum_{\{n', b' : n'+b'>0\}} P(n', b'|1) \int_{\phi'} V(s_{it+1}) dF(\phi'|\phi_{it}, n', b', 1) \tag{2.10}$$

Patent value. In Pakes (1986), the distribution of returns from holding patents is estimated by solving the patentee's optimal stopping problem of whether renewing the patent or not. Introducing patent counts into the productivity evolution enables me to analyse the patent value using a new approach. To obtain the value of patents, we need to condition on firm's R&D investment since R&D is the fundamental source of productivity growth. We then compute the increase in the firm value by adjusting the patent counts. For invention patent, the long-run value is given by

$$\begin{aligned} VP_{inv}(\phi_{it}) = & \ln \underbrace{\left[\sum_{b' \in \{0,1\}} Pr(b'|n_{it+1} = 1) \mathbf{E}V(s_{it+1}|\phi_{it}, 1, b', 1) \right]}_{\text{firm value when an invention patent occurs: } VP^1_{inv}(\phi_{it})} \\ & - \ln \underbrace{\left[\sum_{b' \in \{0,1\}} Pr(b'|n_{it+1} = 0) \mathbf{E}V(s_{it+1}|\phi_{it}, 0, b', 1) \right]}_{\text{firm value if no invention patent occurs: } VP^0_{inv}(\phi_{it})}, \end{aligned} \tag{2.11}$$

where $Pr(b'|n_{it+1} = n')$ is the probability of the event $b_{it+1} = b'$ conditional on

$n_{it+1} = n'$. In a similar way, we can compute the value of an utility patent:

$$VP_{uti}(\phi_{it}) = \ln \underbrace{\left[\sum_{n' \in \{0,1\}} Pr(n'|b_{it+1} = 1)\mathbf{E}V(s_{it+1}|\phi_{it}, n', 1, 1) \right]}_{\text{firm value when an utility patent occurs: } VP^1_{uti}(\phi_{it})} - \ln \underbrace{\left[\sum_{n' \in \{0,1\}} Pr(n'|b_{it+1} = 0)\mathbf{E}V(s_{it+1}|\phi_{it}, n', 0, 1) \right]}_{\text{firm value when no utility patent occurs: } VP^0_{uti}(\phi_{it})}. \tag{2.12}$$

Then the expected firm value when a firm invests in R&D can be decomposed as:

$$\begin{aligned} \mathbf{E}V(s_{it+1}|\phi_{it}, rd_{it} = 1) =& Pr(n_{it+1} = 1)VP^1_{inv} + (1 - Pr(n_{it+1} = 1))VP^0_{inv} \\ =& Pr(b_{it+1} = 1)VP^1_{uti} + (1 - Pr(b_{it+1} = 1))VP^0_{uti}, \end{aligned} \tag{2.13}$$

where the unconditional probabilities $Pr(n_{it+1} = 1) = P(1, 0|1) + P(1, 1|1)$ and $Pr(b_{it+1} = 1) = P(0, 1|1) + P(1, 1|1)$. In principle, the patent value is defined for each firm. Even if this firm does not submit any patent applications, the formulae (2.11) and (2.12) delivers the shadow value of a potential patent. To make the results comparable with existing literature, one can estimate the value of patent focusing on observations with positive counts of patent.

In what follows, I employ the empirical framework to analyze a sample of Chinese high-tech manufacturing firms. I first introduce the data source, then explain the estimation procedures and the estimation results.

2.3 Data

2.3.1 Data sources

Firm-level production data. The first data set contains information on the large and medium sized Chinese manufacturing firms from 2001 to 2007 complied by China's National Bureau of Statistics (CNBS hereafter). This data set is widely used in studies on Chinese firms (See Hsieh and Klenow (2009), Song, Storesletten, and Zilibotti (2011), and Brandt, Biesebroeck, and Zhang (2012) for example). This data set includes all Chinese State Owned Enterprises (SOEs hereafter) and non-

SOEs with annual sales no less than five million *Renminbi* (equivalent to about 700,000 US dollars). These firms accounts for 98% of the manufacturing exports. This data set contains all the information of the firm's major accounting sheets, which includes more than 100 financial variables. Serving for the purpose of this study, it includes firm sales, number of employees, material input, fixed assets, R&D expenditures, and firm characteristics like firm age and its industrial code. In summary, this rich data set provide the information on the firm-level production activities. I have obtained a sample of high-tech manufacturing firms from this dataset.

Patent data. The second database it on patent statistics collected by the State Intellectual Property Office (henceforth SIPO) of China. It contains all the patents that are applied by Chinese firms and certified in mainland China. For each patent the database has the information on its type (invention, utility model, and design), owner, application time, certification time, agent of application, abstract, location, and expiration time during 1985 and 2012. But it should be noted that there is no information on citations for patents in the database, which makes it difficult to measure the patents quality directly. According to China's Patent Law, the utility model refers to a new technical solution suitable for practical use proposed for the shape, construction or combination of the products. Generally, an invention patent is also related to a new technical solution proposed for the product, method or its improvement. But the patenting process for invention patent consists of a "substantive review" which specifically emphasizes on the novelty and originality of the breakthrough in technical upgrading. Obviously, lower creativity standards are enforced for utility model patents. Invention patents, however, may be of less practicability and generate less profits. As for design patents, they represent more rudimentary type of innovation and are considered to be of lower quality than invention patents and utility model patents ().[5] Therefore we anticipate that design patents is less related to firm's productivity. Considering this, I will focus

[5] According to Article 22 of the Patent Law of the P.R.C.: any invention or utility model for which patent right may be granted must possess novelty, inventiveness and practical applicability. In comparison, the requirement for the approving of design patents is in Article 24 of the Patent Law of the P.R.C as "...... must not be identical with or similar to any design which, before the date of filing, has been publicly disclosed in publications in the country or abroad or has been publicly used in the country, and must not collide with any legal prior rights obtained by any other person."

on invention patents and utility patents in the empirical investigation.

Final combined database. For the purpose of this study, I merge these two data sets using the firm name. Table 2.1 shows aggregate information on the number of patents for the combined database. The aggregate number of invention patents and utility patents show a strong increasing trend over the sample period. One important concern on using the combined data set is the efficiency of matching between these two data sets. To evaluate the matching efficiency, in the last row of Table 2.1, I show the percentage of the total number of invention patents in the merged data set to the figure published in the China Statistical Yearbook on Science and Technology. We find that this ratio varies across years, with 55.57% in 2007 and 96.35% in 2003. Overall, the merged data set captures most of the information in the patents data.

Table 2.1: Number of patents in the merged database and matching efficiency

year	2001	2002	2003	2004	2005	2006	2007
invention	1982	4462	5333	7993	10100	17033	19750
utility model	4202	5649	7496	7798	10720	15324	18212
matching	57.10%	81.26%	96.35%	87.20%	57.58%	67.33%	55.67%

Note: matching efficiency refers the ratio of number of invention patents in the merged data set to the published figure in China Statistical Yearbook on Science and Technology 2001-2007.

2.3.2 Descriptive statistics

China's high-tech industries mainly covers four 2-digit industries: pharmaceutical manufacturing, special equipment, electric machinery, and electronics. In Table 2.2 I report the summary statistics for the R&D and patenting activities in the final dataset. The average R&D expenditure for high-tech manufacturing firms is 218.095 thousand yuan (equivalent to around 31,584 US dollars). The R&D intensity measured by total R&D expenditures over total sales is relatively low than that reported for developed countries. Lastly, compared to the R&D participation, we observe that the probability of generating a patent is much lower.

In Figure 2.1, I display the number of firms for each 2-digit high-tech industry by their innovative activities. As shown in Figure 2.1, even for the high-tech

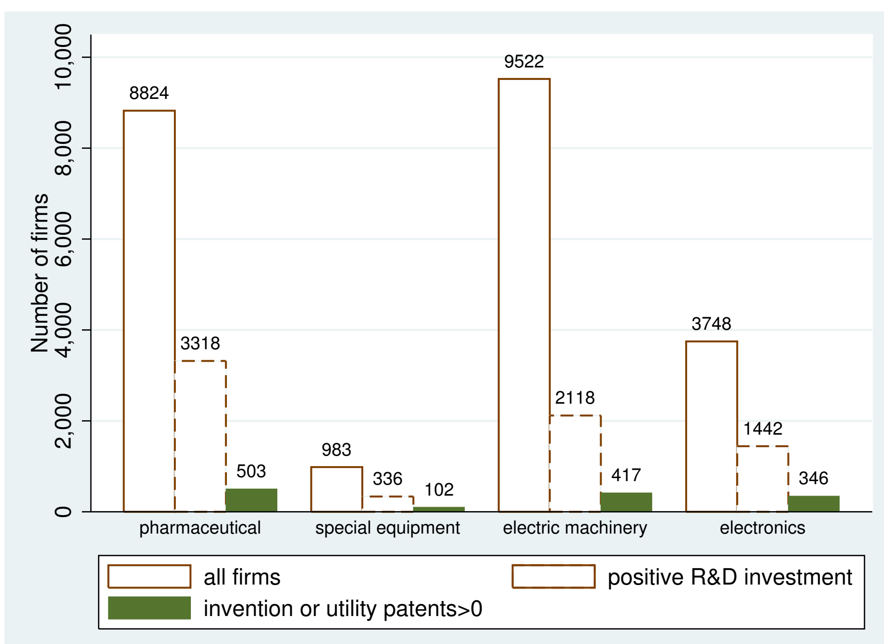
Table 2.2: Summary statistics for high-tech and non-high-tech industries

	High-tech		Non-high-tech	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
R&D expenditures	218.095	963.152	34.886	326.677
R&D/employees	1.794	8.327	0.282	4.686
R&D/sales	0.007	0.024	0.001	0.008
Pr(R&D>0)	0.289	0.454	0.106	0.307
Invention patents	0.056	0.776	0.010	0.306
Utility patents	0.083	1.058	0.028	0.376

Note: the unit of R&D expenditure is 1,000 yuan (around 150 US dollars).

manufacturing firms in China, only a small portion of firms undertake R&D investment. The fraction of firms that file patent applications is even smaller. The difference between R&D activities and patent applications imply that distinguishing the input of innovation and output of innovation is important when thinking of the costs and benefits of innovation because R&D activities with patents may generate larger impact on the firm's productivity. The decline in the number of firms also suggests that innovative firms face uncertainty in generating patents.

Figure 2.1: Number of Firms by Innovation Activities



Note: numbers are from the final database

I also notice that in the data, the extensive margins of R&D and patents capture a majority of the innovation activity. These data features are presented in the data appendix. Moreover, Mairesse, Mohnen, and Kremp (2005) provide evidence on the substantial measurement error of using R&D expenditure to predict the innovation probability for the firm-level data from the French innovation survey. Also Chen, Liu, Serrato, and Xu (2017) also document that corporate income tax reductions induce Chinese firms to relabel administrative expenses as expenditures on R&D. These results suggest that the levels of R&D may not accurately reflect the firm's actual investment in innovation. Therefore using discrete R&D choice as a measure of R&D investment can also help decrease measurement error.

2.4 Estimation and Results

The empirical method I use is the same as PRVF. The difference is that I include both R&D and patents in estimating the equation for productivity evolution. In analyzing the estimation results, I focus on the decomposition of R&D benefits and the value of patents. To simplify the notation, I will omit time and firm subscripts whenever no confusion arises. Moreover, Z' represent the next-period Z, and $z = \ln(Z)$.

2.4.1 Productivity estimation

Revenue equation. I parameterize the productivity process as a cubic function of lagged productivity:

$$\begin{aligned}\phi_{it+1} =& \rho_0 + \rho_1 \phi_{it} + \rho_2 \phi_{it}^2 + \rho_3 \phi_{it}^3 \\ & + \rho_4 d_{it} + \rho_5 \left(n_{it+1} \times rd_{it}\right) + \rho_6 \left(b_{it+1} \times rd_{it}\right) + \varepsilon_{it+1}\end{aligned} \tag{2.14}$$

where the first line on the right-hand side captures the persistence of productivity, the second line describes the impacts of R&D and patents on the evolution of productivity. It is clear that the effect of past R&D activity on current future productivity is affected by the creation of new ideas. We expect that ρ_5 and ρ_6 are different from each other because different types of patents represent different forms of realized innovation. To a large extent, the invention patents are more related to product innovation, while the utility patents are more related to process innovation. These parameters give us information on the quality of patents (or ideas) to some extend. For example, when $\rho_5 > \rho_6$, invention patents have a larger impact on enhancing the productivity.

I estimate the productivity using the first-order condition of materials.The demand for materials is dependent on the observed capital stock, age, and unobserved productivity. This gives us an expression for the productivity:

$$\phi_{it-1} = \left(\frac{1}{1-\sigma}\right)\beta_{t-1} + \beta_k k_{it-1} + \beta_a a_{it-1} - \frac{1}{1-\sigma} m_{it-1} \tag{2.15}$$

where β_t represents the the intercept of the CES demand function and the price of variable inputs common to all firms. Combining (2.15) and (2.14) and plugging them into (2.1) yields an empirical equation for the firm revenue:

$$\begin{aligned} r_{it} =& (1-\sigma)\beta_k k_{it} + (1-\sigma)\beta_a a_{it} \\ & - \rho_1\left[\beta_{t-1} + \beta_k(1-\sigma)k_{it-1} + \beta_a(1-\sigma)a_{it-1} - m_{it-1}\right] \\ & - \frac{\rho_2}{1-\sigma}\left[\beta_{t-1} + \beta_k(1-\sigma)k_{it-1} + \beta_a(1-\sigma)a_{it-1} - m_{it-1}\right]^2 \\ & - \frac{\rho_3}{(1-\sigma)^2}\left[\beta_{t-1} + \beta_k(1-\sigma)k_{it-1} + \beta_a(1-\sigma)a_{it-1} - m_{it-1}\right]^3 \\ & - (1-\sigma)\left[\rho_4 rd_{it-1} + \rho_5(n_{it} \times rd_{it-1}) + \rho_6(b_{it} \times rd_{it-1})\right] + \mu_0 + \mu_t + v_{it} \end{aligned} \tag{2.16}$$

where $v_{it} = u_{it} - (1-\sigma)\varepsilon_{it}$, with u_{it} being the measurement error to the revenue and exogenous to the firm's decisions on choosing variable inputs or investment in R&D. The estimation of (2.16) relies on the condition that the composite error v_{it} is uncorrelated with all the explanatory variables on the right-hand side. μ_0 is an intercept which combines constants from the revenue function and the productivity process. μ_t and β_{t-1} are functions of the common time-varying variables including the demand intercept and factor prices. The higher-order powers on ϕ_{it-1} enables us to distinguish β_{t-1} from μ_t and identify up to a base-year normalization. They also serve as an approximation to a general non-linear productivity process. To account for the differences in the revenue functions and the demand elasticity, μ_0 is interacted with industry dummies. Once I obtain the estimates of β_{t-1}, β_k, β_a, I can recover the productivity using Equation (2.15). Then ρ_0 can be estimated using the mean zero moment condition for ε_{it}. We employ a two-step estimation strategy. In the first step, I estimate the demand elasticity. In the second step, I replace σ with its estimates and estimate (2.16) using the Non-linear Least Square estimator.

Demand elasticity. For each industry, note that the ratio of total variable costs to firm revenue VC/R is equivalent to $(1-1/\sigma)$. Therefore, for industry j, we can estimate σ by using the average of the ratio of variable costs to revenue:

$$\hat{\sigma}_j = -\frac{\sum_{it} R_{it}}{\sum_{it}(VC_{it} - R_{it})} \tag{2.17}$$

Table 2.3 reports the estimation results. Notice that σ varies across industries. For the electronics industry, the estimate of σ is 6.34, the corresponding markup is 1.187. In comparison, for the machinery industry, the demand elasticity is estimated to be -5.043, implying the a markup of 1.247. We can also find that the estimates of σ are smaller than that obtained by Peters et al. (2017) using German data. This may imply that Chinese high-tech firms have a lower markup than Germany high-tech firms.

Table 2.3: Estimates of demand elasticities

industry	pharmaceutical	equipment	electronics	machinery
$\hat{\sigma}$	5.926	5.043	6.341	5.415
$\frac{\hat{\sigma}}{\hat{\sigma}-1}$	1.203	1.247	1.187	1.227

Productivity evolution equation. I plug the estimates of σ into (2.16) to estimate the parameters for the productivity evolution equation. Table 2.4 reports the full estimation results. Column (1) shows the estimation results of including rd_t, $n_{t+1} \times rd_t$, and $b_{t+1} \times rd_t$ in addition to 3d order polynomials of current productivity. The estimation results show the impact of R&D on productivity hinges on the patenting activities. Note that the marginal effect of rd_t on the expectation of future productivity is $\rho_4 + \rho_5 n_{t+1} + \rho_6 b_{t+1}$, the estimates of which are as follows:

$$\frac{\Delta \mathbf{E}\left(\phi_{t+1} | \phi_t, rd_t\right)}{\Delta rd_t} = .00435 + .0145 \times n_{t+1} + .0137 \times b_{t+1}$$

This indicates that patents play an important role in enhancing the productivity effect of R&D. If we think of a firm with positive investment in R&D in current period, then the expected increase in productivity would be $\frac{.0145}{.00435} \approx 3.33$ times greater if it can produce an invention patent in future period and $\frac{.0137}{.00435} \approx 3.15$ times greater if it produces an utility patent in next period.

Table 2.4: Estimates of productivity evolution equation and cost function

	cubic parameterization	
Productivity evolution		
rd_t	.00435**	(2.90)
$n_{t+1} \times rd_t$	.0145**	(2.90)
$b_{t+1} \times rd_t$	.0137*	(2.76)
ϕ_t	.824**	(14.96)
ϕ_t^2	.503**	(2.69)
ϕ_t^3	-1.135**	(-14.26)
ρ_0:		
common part	.0295**	(8.34)
Pharmaceutical	-.0144*	(-3.90)
Electronics	-.0132**	(-3.61)
Electric Machinery	-.0116**	(-2.92)
σ_ε	.10	
Cost function		
k	-.0299**	(-25.82)
$a \in (10, 19)$	.0740**	(12.62)
$a \in (20, 49)$	0.111**	(12.88)
$a \geq 50$	.149**	(7.84)
sample size	22492	

Note: T statistics are in parentheses; * p<0.05, ** p<0.01.

In the model, patents are channels through which R&D spurs the productivity growth. This is different from the PRVF model in which the impact of R&D on future productivity is fully captured by realized process or product innovation. PRVF find that the coefficient of realized process innovation is 0.029 and that of realized product innovation is 0.036 for German high-tech firms. Our results are smaller than these estimates if we consider invention patents as realized product innovation while utility patents as realized process innovation. This implies that the productivity-growth effect of realized innovation is smaller for Chinese firms.

For the endogenous productivity approach, an implicit condition for a firm to be active in innovative activities is that the productivity cannot increase or decrease too fast in order for it to innovate. Otherwise, the productivity is unbounded in the future, which discourages firms from investing in R&D. The estimation results show that the revenue productivity is between -0.454 and 0.817, which implies that the absolute value of first-order derivative of expected future productivity with respect to current productivity is less than one, thus satisfying the requirement for the value function estimation. In the appendix, I display the range of this slope. I also try a quadratic specification in which only the first- and second-order of ϕ_t are included. However, in this case, the fraction of observations that violates this assumption is not negligible; the corresponding results are displayed in appendix B.2.2.

2.4.2 R&D-patents relation

By formulating the R&D-patent linkage as a conditional joint cumulative distribution function, we implicitly account for the correlation between invention patents and utility patents. This can be caused by the idea diffusion within the firm. We also expect that firms engaging in R&D activities are more likely to produce invention or utility patents. Lastly, we do not model the possibility that different firms have different inclination to protect their ideas by creating patents. By selecting high-tech industries, we try to alleviate the concern that some firms may not want to protect their innovation via patenting because high-tech firms are more willing to file patent applications when they create new ideas. In addition, our sample period starts from 2002, before which China has implemented several amendments to patents law aimed to strength the protection of intellectual property rights (Hu and Jefferson, 2009). As a result, our measure is an average of the industry-specific propensity of submitting patent applications.

We estimate the probability of producing applicable patents conditional on the firm's past R&D status. For notation simplicity, $P\left(n_{t+1} = n', b_{t+1} = b' | rd_t\right)$ is denoted as $P\left(n', b' | rd_t\right)$. For each industry, our estimator for the conditional probabilities is given by

$$\hat{P}\left(n', b'|d\right) = \frac{\sum_i \sum_t \mathbb{I}\left(n_{it+1} = n'\right) \mathbb{I}\left(b_{it+1} = b'\right)}{\sum_i \sum_t \mathbb{I}\left(rd_{it} = d\right)} \tag{2.18}$$

where $\mathbb{I}(\cdot)$ is the indicator function and $n', b', d \in \{0, 1\}$. This procedure imposes that the probability of filing patent applications only depends on the firm's past R&D activity. Moreover, the technology of generating patent applications is common to all firms within the same industry.

The results are displayed in Table 2.5. We can find that these probabilities are different in different industries. While the pharmaceutical industry is better at producing invention patents, the other three industries create more utility model patents. This may imply that product innovation is more prevalent in pharmaceutical industry, but the process innovation is more common in other high-tech industries. Last but not the least, there is a certain probability that product innovation is discovered along with process innovation.

Table 2.5: Distribution of patent applications conditional on R&D decision

Industries	$p(0,0)$	$p(1,0)$	$p(0,1)$	$p(1,1)$
pharmaceutical	0.903	0.085	0.007	0.005
equipment	0.826	0.012	0.115	0.047
electronics	0.899	0.009	0.069	0.023
machinery	0.857	0.015	0.094	0.035

Note: $p(x,y) = Prob(n_{t+1} = x, b_{t+1} = y | rd_t = 1)$.

2.4.3 R&D costs and benefits

we can express the firm's probability of investing in R&D as:

$$\begin{aligned} Pr(rd_t = 1|\phi_t, rd_{t-1}) =& Pr\left[\Delta EV(\phi_t, rd_{t-1}) \geq C_{it}\right] \\ =& 1 - \exp\left[-\frac{\beta}{\gamma}(\mathbf{E}V_1 - \mathbf{E}V_0)\right] \end{aligned} \tag{2.19}$$

where the second equality comes from the assumption that the R&D costs follow an exponential distribution. Knowing (κ_s, κ_m) allows us to characterize the distribution of R&D costs given the information on capital stock and past R&D choice. Equation (2.19) indicates that β can not be separated from γ without additional assumption. Therefore we employ the annual deposit rate to set the value for β. Let $\bar{R}$ be the average real annual deposit rate. The annual real deposit rate is cited from Song et al. (2011) and $\bar{R} = 1.1075$, we choose $\beta = 1/1.0175 = 0.983$.

I follow Rust (1987) to apply the nested fixed point algorithm to estimate the dynamic discrete choice model. To implement this algorithm, we discretize the productivity space into 100 grid points, the capital stock into 50 grid points. Remember that we have 4 categories of ages and two states for past R&D experience. Therefore, we estimate the value function for $100 \times 50 \times 4 \times 2 = 40000$ types of firms. I use the methodology proposed by Farmer and Toda (2017) to discretize the non-linear Markov process specified for the productivity evolution. Finally, we assume that the costs are i.i.d across all firms and periods, then the cost parameters can be estimated using the Maximum Likelihood Estimator (MLE) obtained by solving following problem:

$$\max_{(\kappa^m,\kappa^s)} \left\{ \sum_{i}^{N} \sum_{t}^{T_i} \log \left[rd_{it} Pr(rd_{it} = 1 | \phi_{it}, rd_{it-1}) + (1 - rd_{it}) Pr(rd_{it} = 0 | \phi_{it}, rd_{it-1}) \right] \right\} \tag{2.20}$$

where N is the sample size of the firm, T_i is the number of periods in which firm i exists in the data. The details of computation and data processing before undertaking the computation are presented in the appendix of computation.

In Panel A of Table 2.6, I display the estimation results of the cost parameters (κ_s, κ_m). In all of the four high-tech industries, we find that the start-up costs of investing in R&D are over ten times larger than the maintenance costs. The estimates also show much differences in the maintenance costs and start-up costs for different high-tech industries. The electronics industry has the largest start-up costs and maintenance costs. This is consistent with that developing new technologies and new ideas on producing electronic products requires relatively more R&D investment either in terms of starting R&D activities or maintaining innovation. On the other hand, the pharmaceutical industry has the lowest start-up costs while the machinery sector has the least the maintenance costs in continuing R&D. However, one caveat about the interpretation of the results is that our estimates of the costs have taken the government's subsidy on R&D activities into consideration. This may bias the estimates downward, and the severity of the bias will be positively correlated to the actual amount of subsidy received by the firms in the sample.

To see these results more clearly, I also translate these estimates into average R&D costs. The average R&D costs is calculated by plugging the average capital stock into the equation of the mean of R&D cost distribution. This measurement also takes the average size of firms in the industry into consideration. I report the results in Panel B of Table 2.6. The average starting costs lie between .797 million US dollars for pharmaceutical industry to 2.241 million US dollars for the electronics industry. While the maintenance costs range from 87 thousands of US dollars to 143 thousands of US dollars. The difference in the magnitudes of start-up costs and maintenance costs help explain the high persistence in the R&D investment.

Table 2.6: Estimation results of R&D costs

Panel A : Estimates for the costs parameters				
Sectors	Pharmaceutical	Equipment	Electronics	Machinery
κ_s	.8981	1.7503	2.7031	1.1807
	(.0351)	(.2928)	(.1249)	(.0792)
κ_m	.1142	.1080	.1727	.1063
	(.0013)	(.0040)	(.0027)	(.0018)
LLF	-4298.48	-360.44	-3354.62	-1611.94
sample size	8603	939	9308	3604
Panel B :Average R&D costs				
Start-up cost	0.797	1.450	2.241	0.966
Maintenance cost	0.101	0.089	0.143	0.087

Note: Standard errors in the parenthesis are obtained by bootstrapping 100 times. Money units are in million US dollars.

2.4.4 Model fitness

The model contains several pieces and are estimated in different stages. I first check the model fitness of the revenue equation by showing the closeness between the revenue predicted by our model and that in the data. In addition, the dynamic model can generate optimal R&D choice given the firm type observed in the data. I compare the model-predicted R&D activities with that in the data from two aspects: first, as a cross-section check, I consider the probability of investing in R&D; second, I also check to what extent the model generated transition dynamics for R&D fits the data. Overall, the estimated model provides a good match for these moments in the data, giving us confidence to perform further structural analysis on the benefits of R&D and patents. The details of these checks on the model fitness are presented in the appendix.

2.4.5 Benefits of R&D investment

2.4.5.1 Aggregate results

The short-run benefits of R&D investment is directly reflected by the changes in productivity, which ultimately influences sales and profits in subsequent periods. In comparison, the long-run gains of R&D can be captured by the changes in the firm's expected future value.r[6] I also report the absolute change in firm value to evaluate the long-run benefits of R&D more completely. Note that the measure of benefits is independent of past R&D activities. However, past R&D activities will affect the current innovation choice jointly with the expected benefits from investing in R&D. I present the estimation results in Table 2.7. We can find that the percentage change caused by R&D investment ranges from 0.0287 % to 0.0330 %. On average R&D investment causes around 0.031 % increase in the annual revenue.

Despite that the increase in the firm's annual sales is relatively small. The effect of R&D is amplified in the long-run. The estimation results show that innovation spurs around 0.45% increase in the firm value, with electronics industry the highest (0.508%) and pharmaceutical industry the lowest (0.382%). The median of the long-run benefits is close to the mean value, indicating that the distribution is not very skewed. Looking at the absolute change in firm value, we know that on average the investment in innovation increases the firm value around 0.235 million USD for Chinese high-tech firms. Different high-tech industries display different returns

[6]Note that under the CES demand structure, the proportional change in the profits is the same as that in revenue.

Table 2.7: Short-run and long-run benefits of R&D investment

sectors	Pharm.	Equip.	Elect.	Mach.	Average
I.Short-run:					
Δ pct.	0.0287	0.0300	0.0330	0.0302	0.031
II.Long-run:					
Δ pct.					
mean	0.382	0.464	0.508	0.470	0.452
median	0.378	0.477	0.492	0.478	
std	0.133	0.122	0.193	0.146	
Δ abs.					
mean	0.200	0.201	0.287	0.191	0.235
median	0.185	0.190	0.252	0.178	
std	0.098	0.086	0.170	0.088	

Note: the absolute change is measured in million USD; the average is a weighted average using the sample size.

to R&D. On average, firms operating in the electronics sector increases their firm value by 0.287 million USD from R&D investment, while this number is 0.191 in the machinery industry. I also notice that the median value is slightly lower than the mean, implying that the distribution is slightly right-skewed. Interestingly but not surprisingly, the benefits of R&D investment in Chinese high-tech industries are estimated to be much lower than that obtained for German high-tech firms. This may reflect a higher degree of uncertainty facing the firm's productivity evolution is taken into consideration in the calculation of long-run firm value. In PRVF, the median of the absolute change in firm value for high-tech industries in Germany ranges from 2.331 million euros to 6.770 million euros. The lower private return to investment in R&D speaks for the less willingness for Chinese firms to participate in innovation activities, which is confirmed by the fact that most of the Chinese high-tech firms do not innovate.

2.4.5.2 Decomposing the benefits of R&D

Based on formulas (2.9) and (2.10), I decompose the benefits of R&D into four components: (1) no patent; (2) only invention patent; (3) only utility patent; (4) both invention and utility patent. In Table 2.8 I present the average of R&D

benefits for each high-tech industry both measured by proportional change and absolute change in the firm value. As a reference, I also display the mean of total R&D benefits in the row titled as 'total'. The results consistently show that creating patents increases the benefits of innovation dramatically. Take the pharmaceutical industry for instance, when there is no patent application, the proportional change in firm value is 0.329%, and the absolute change in firm value is 0.173 million USD. In sharp contrast, when invention patents and utility patents occur, the corresponding change becomes 1.368% and 0.709 million USD. This large difference implies that the patenting activity comprises an important component of innovation that contributes to the private return to R&D.

Table 2.8: Decomposition of the Long-run benefits of R&D investment

	Pharmeceutical	Equipment	Electronics	Machinery
proportional change:				
no patent	0.329	0.376	0.437	0.384
invention	0.852	0.788	1.027	0.882
utility	0.823	0.765	0.994	0.854
both	1.368	1.191	1.609	1.369
total	0.382	0.464	0.508	0.470
absolute change:				
no patent	0.173	0.164	0.249	0.157
invention	0.443	0.339	0.571	0.356
utility	0.428	0.329	0.553	0.345
both	0.709	0.509	0.889	0.551
total	0.200	0.201	0.287	0.191

Note: the absolute change is measured in million USD.

Our previous results, however, do not take the uncertainty of the realization of different states into account. To understand more about the relative importance of each component of the innovation activities, I multiplying each component of R&D benefits by their probability of realization in Table 2.9. Note that by multiplying the probability, we are able to track the exact contribution of each component in realizing the benefits of R&D investment. Not surprisingly, for all high-tech industries the case when there is no patent application is the largest component in the benefits of R&D because of the large probability for firms to encounter this situation. As for the importance of creating invention patents or utility patents, their relative importance differs in different industries. This is mainly driven by the difference in probabilities $Pr(n_{t+1} = n', b_{t+1} = b')$. On average, we find that non-patenting R&D investment accounts for around 70% of returns to R&D, implying that the realization of a large of part of the R&D benefits come from non-patenting activities. For pharmaceutical industry, the relative importance of invention patents is 19.0%, while for other high-tech industries, the contribution of invention patents is around 2%. In contrast, the contribution of utility patents in these industries is over 13%, much larger than 1.6% for the pharmaceutical industry. This is because firms in the pharmaceutical industry have higher chance of creating invention patents than firms in other high-tech industries.

Table 2.9: Decomposition of the Long-run benefits of R&D investment: relative importance

	Pharmaceutical	Equipment	Electronics	Machinery
no patent	0.777	0.669	0.774	0.699
invention	0.190	0.020	0.018	0.028
utility	0.015	0.190	0.135	0.171
both	0.018	0.121	0.073	0.102

Note: each column adds up to one.

2.4.6 Value of patents

I employ (2.11) and (2.12) to calculate the value of patents. In principle, the value of patents is defined for each firm. Even if this firm does not file patent applications, our formula gives the shadow value of potential patents. To make the results comparable with the literature, I only estimate the value of invention (utility model) patents focusing on the observations with positive invention (utility model) patents. That is, the patent value is reported only when the firm files some patent applications. The estimation results are displayed in Table 2.10. We can see that invention patents and utility model patents play a significant role in increasing the firm value. Take the pharmaceutical industry for example, the mean value of proportional increase in firm value caused by creating an applicable invention patent is 0.547%, and the associated mean of absolute change is 0.283 million

USD. In comparison, the mean of proportional increase in the firm value caused by creating an utility patent is 0.674%, which is corresponding to an increase of 0.349 million USD in the firm value. On average, an invention (utility) patent causes 0.764% (0.666%) increase in the firm value. Hence the value of a patent is about twice as much as the benefits of R&D investment. In addition, note that the value of invention patents is smaller than utility patents in the pharmaceutical industry, while the situation is reversed in other three high-tech industries. This results is mainly driven by the relatively high probability of producing invention patents in the pharmaceutical industry. Since the largest gain from R&D investment comes from the situation when the firm generates both invention and utility patents, the conditional probability $Pr(b_{t+1} = 1|n_{t+1} = 1, rd_t = 1)$ is also an important factor in explaining the value of patents. In pharmaceutical industry, the conditional probability is only 0.056, being much lower than other high-tech industries.

Table 2.10: Estimates of the value of patents

	invention			utility		
	mean	median	std	mean	median	std
proportional change:						
Pharmaceutical	0.547	0.552	0.180	0.674	0.681	0.219
Equipment	0.683	0.721	0.155	0.505	0.534	0.116
Electronics	0.963	0.974	0.304	0.701	0.709	0.223
Machinery	0.788	0.823	0.216	0.598	0.625	0.166
average	0.764			0.666		
absolute change:						
Pharmaceutical	0.283	0.266	0.126	0.349	0.328	0.154
Equipment	0.291	0.285	0.101	0.215	0.210	0.075
Electronics	0.529	0.483	0.251	0.385	0.351	0.184
Machinery	0.317	0.306	0.128	0.241	0.232	0.098
average	0.391			0.341		

Note: value of invention (utility) patents is only reported for observations with invention (utility) patents; the absolute change is measured in million USD.

The patent value measured by our model captures the proportional changes in the firm's value conditioning that the firm has investment in R&D in current period. In this sense, the production-based measure is more related to the private value of patents instead of their social benefits, which are realized through knowledge spillovers.[7]

2.5 Analysis of Different R&D Subsidy Policies

The model provides a lens to understand the impact of certain policies targeting at improving the firm's investment in innovation. In this section, I analyze the impacts of two different R&D subsidy policies that are currently implemented in China. The first type of policy is the R&D cost reduction through lowering the financing costs for R&D. For this case, I consider it as proportional reductions either in start-up costs or in maintenance costs. The second type of the policy is a lump-sum transfer to the firm that decides to undertake investment in R&D. Similarly, we also consider whether this lump-sum transfer is given to firms starting investing in R&D or to firms for maintaining their R&D activities. To evaluate these policies, I look at how these policies affect the innovation probability and the change in firm value by conducting several experiments based on the estimated structural model.

2.5.1 Formulation and cost-benefit analysis

Basic formulation. Let $(1-\delta_s)$ (or $(1-\delta_m)$) be the reduction rate caused by the R&D subsidy to start-up costs (or maintenance costs). After the proportional R&D subsidy, in period t the mean of the cost distribution facing a firm is $\gamma_t(s) = \delta_s\kappa_m(rd_{t-1})k_t + \kappa_s(1-rd_{t-1})k_t$ (or $\gamma_t(m) = \kappa_s rd_{t-1}k_t + \delta_m(1-rd_{t-1})k_t$). For $\tau \in \{s, m\}$, consider a one-period reduction in the R&D costs, the firm's value function can be reformulated as:

$$W_\tau(\phi_t, rd_{t-1}) = \pi(\phi_t) + \int_0^\infty \max_{rd_t\in\{0,1\}} \{\beta\mathbf{E}V_0, \beta\mathbf{E}V_1 - c\}\, dG_\tau(c) \tag{2.21}$$

where $G_\tau(c) = 1-\exp(\frac{c}{\gamma_t(\tau)})$ is the cumulative density function for the exponential distribution with a mean of $\gamma_t(\tau)$. Using this formulation, we are able to cap-

[7] A widely used indicator for patent quality is patent citations. However, China's patent data are lack of patent citations. Dang and Motohashi (2015) propose to use the measure of knowledge breath as a proxy for the quality of patents. In appendix B.2.4, I show that this method may not be a good indicator for the patent quality. At least, it does not reflect the private value of patents measured as increasing the firm's value.

ture the effect of implementing proportional subsidy on the firm value. Based on the estimates of $\mathbf{E}V_0$ and $\mathbf{E}V_1$ from the previous computation, we can calculate $W_\tau(\phi_t, rd_{t-1})$.

To make these two subsidy programs comparable, we choose two parameters such that $(1-\delta_s)\kappa_s = (1-\delta_m)\kappa_m$, or equivalently,

$$\delta_s \equiv 1 - \frac{(1-\delta_m)\kappa_m}{\kappa_s} \tag{2.22}$$

Now we turn to consider the impact of lump-sum transfer, let us denote F as the lump-sum transfer given by the government if the firm undertakes R&D investment. Then the firms value function becomes:

$$W_\tau^F(\phi_t, rd_{t-1}) = \pi(\phi_t) + \int_0^\infty \max_{rd_t \in \{0,1\}} \{\beta \mathbf{E}V_0, \beta \mathbf{E}V_1 + F_t(\tau) - c\}\, dG(c) \tag{2.23}$$

where $F_t(\tau) = rd_t \times F$ if $\tau = m$ and $F_t(\tau) = (1 - rd_t) \times F$ if $\tau = s$, where $F = (1-\delta_m)k_t$. Note that our formulation differs from the subsidy program of corporate income tax cuts considered by Chen et al. (2017) in the sense that the amount of subsidy is not directly related to the corporate income. Therefore, we evaluate these two policies under the circumstance in which the government spending is constant whenever a firm receives the subsidy. We calculate W_τ and W_τ^F choosing δ_m to be 0.90, 0.85, and 0.80.

Finally, based on these characterization, the long-run effect of one-period government subsidy on the firm's value is estimated as:

$$LB_\tau(\phi_t, rd_{t-1}) = W_\tau(\phi_t, rd_{t-1}) - V(\phi_t, rd_{t-1}) \tag{2.24}$$

$$LB_\tau^F(\phi_t, rd_{t-1}) = W_\tau^F(\phi_t, rd_{t-1}) - V(\phi_t, rd_{t-1}) \tag{2.25}$$

The improvement in firm value through R&D subsidy is then calculated as the sample averages of these two variables. Similarly, we define the change in the average probability of innovation after subsidy as $P(\tau)$ and $P^F(\tau)$; their full expressions are presented in the math appendix.

Costs-benefits analysis on the R&D subsidy. The costs-benefits analysis refers to the change in firm's value caused by one-unit subsidy on R&D activities. Recall that we have chosen the subsidy policy parameters such that the expenditures of different programs are identical for the same firm conditional on the firm's eligibility for the subsidy. However, the expected total expenditure can still be different because different subsidy polices gives different incentives for firms to innovate. When aggregated, the total actual expenditures become different for different subsidy programs. This leads us to evaluate the innovation effect per unit subsidy. The change in firm value caused by a unit subsidy is given as:

$$\chi_\tau = \frac{1}{NT}\sum_i\sum_t \underbrace{G_\tau(\mathbf{E}V_1 - \mathbf{E}V_0)}_{\text{innovation prob.}} \times \underbrace{\frac{LB_\tau(\phi_t, rd_{t-1})}{(1-\delta_m)\kappa_m k_t}}_{\text{benefit per unit subsidy}} \tag{2.26}$$

$$\chi_\tau^F = \frac{1}{NT}\sum_i\sum_t \underbrace{[G_\tau(\mathbf{E}V_1 - \mathbf{E}V_0) + F_\tau]}_{\text{innovation prob.}} \times \underbrace{\frac{LB_\tau^F(\phi_t, rd_{t-1})}{(1-\delta_m)\kappa_m k_t}}_{\text{benefit per unit subsidy}} \tag{2.27}$$

It is worth noting that χ_τ and χ_τ^F measure the change in firm value caused by one unit proportional subsidy or lump-sum subsidy, respectively. The relative magnitude of χ_τ to χ_τ^F implies the relative efficiency of proportional subsidy to lump-sum subsidy. More specifically, $\chi_\tau > \chi_\tau^F$ ($< \chi_\tau^F$) implies that proportional subsidy is more (less) efficient than lump-sum subsidy in terms of increasing the firm value. Similarly, we can define the change in the innovation probability of all firms caused by one unit subsidy. To save space, I put these expressions in the math appendix.

2.5.2 Results

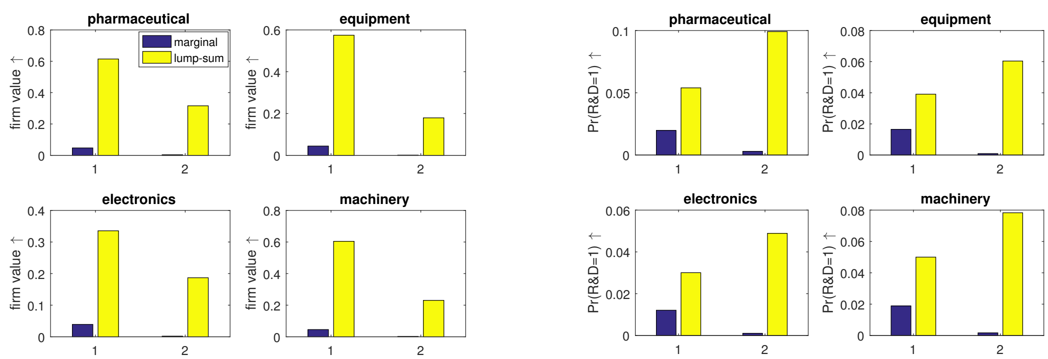
I conduct three groups of experiments by choosing $\delta_m = 90\%$,85%, and 80%. All results in these experiments display similar results on the relative effectiveness of the R&D subsidy policy. For the sake of brevity, I report the results of the experiment in which $\delta_m = 80\%$.[8]

Increase in firm value and innovation probability. We first show the results of change in firm value caused by subsidizing the R&D costs. In Panel A of Figure 2.2, the blue bar represents the average effect of proportional subsidy while the yellow bar the average effect of lump-sum subsidy. In all the graphs, '1' and '2' represent the subsidy on the maintenance costs and start-up costs, separately. There are

[8]All the results for other experiments are relegated to appendix B.2.5.1.

several interesting findings from this experiment. First, lump-sum subsidy is much more effective than proportional subsidy in enhancing the firm value for all the Chinese high-tech industries. Second, the effectiveness of subsidy policy differs in different industries. Third, reductions in the maintenance costs have a larger impact on increasing the firm value than that of decreasing the start-up costs. This implies that financing the maintenance costs of innovation is more effective than financing the start-up costs of innovation if the objective of the policy maker is to enhance the firm value.

Figure 2.2: Impacts of different R&D subsidy policies: $\delta_m = 0.80$



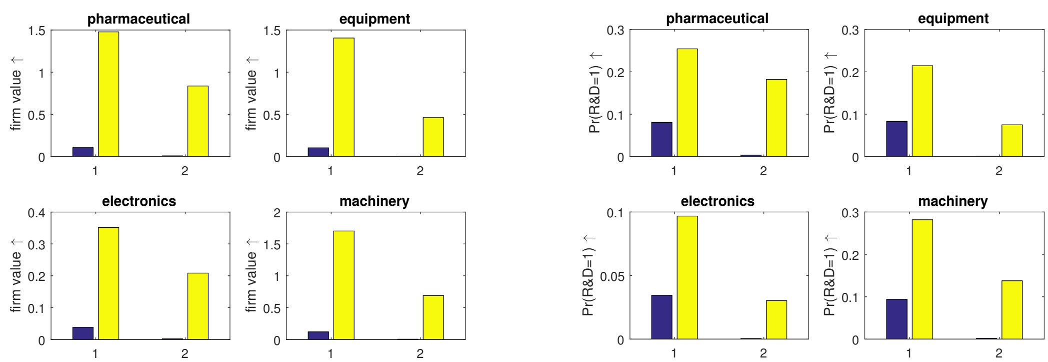
Panel A. Firm value　　　　Panel B. Innovation prob.

Note: in all the graphs, '1' represents subsidy on the maintenance costs, '2' represents subsidy on the start-up costs. Firm value is measured in 10,000 US dollars.

Furthermore, we display the results on the impact of R&D subsidy on innovation participation in Panel B of Figure 2.2. Now the implication of the results becomes different. We have following important observations from the results. First, for all the industries, lump-sum subsidy is more effective than proportional subsidy. Second, different subsidy programs have different impact on increasing the innovation probability when implemented for different types of R&D costs. For the proportional subsidy, reducing the maintenance costs is more effective in enhancing the probability of investing in R&D. However, lump-sum subsidy is found to be more effective when financing the start-up costs of R&D investment. Note that these results are dependent on the assumption of the distribution of R&D costs as well as the distribution of the states.

The effect of one unit R&D subsidy. To investigate the cost-benefit efficiency of R&D subsidy, we further compute the increase in firm value and/or innovation participation caused by one unit expenditure on R&D subsidy. The results are displayed in Figure 2.3 . We can find that: first, lump-sum subsidy is more efficient than proportional subsidy either for increasing the firm value of increasing the innovation participation. Second, subsidizing the maintenance costs is more efficient. It is worth mentioning that these counterfactual results depend on the the functional forms chosen in our structural model. However, they do show that lump-sum transfer works better by increasing the expected benefits of innovation uniformly.

Figure 2.3: Impacts per unit R&D subsidy: $\delta^m = 0.80$



Panel A. Firm value

Panel B. Innovation prob.

Note: in all the graphs, '1' represents subsidy on the maintenance costs, '2' represents subsidy on the start-up costs. Firm value is measured in 10,000 US dollars.

2.6 Conclusion

Understanding the costs and benefits of R&D investment is crucial for the designing of innovation policy in spurring R&D investment. The benefits of R&D are realized through different channels. Even in the presence of innovation failure, R&D investment can still promote the firm's productivity through knowledge accumulation. Since it is hard to find a perfect measure for the innovation outcome, including R&D in addition to innovation outcome in evaluating the benefits of innovation is necessary for obtaining more accurate estimates for the benefits of R&D.

By allowing a flexible relationship between innovation and productivity, this paper proposes an empirical framework to decompose the benefits of R&D into patent and non-patent channels. The structural model extends an existing framework to incorporate both input and output of innovation into the evolution of productivity. Applying it to a sample of Chinese high-tech manufacturing firms, I find that Chinese high-tech firms generate much lower benefits from innovation than existing estimates of high-tech firms in Germany. More interestingly, most of the benefits of R&D investment originates from non-patenting R&D investment. The estimation framework also provides a new approach for estimating the value of patents. Based on the structural estimates, I perform a series of counterfactual analysis to evaluate the effectiveness of different R&D subsidy schemes. Overall, the results suggest that lump-sum transfer is more efficient than the marginal subsidy.

Chapter 3

Types of Patents and Driving Forces behind the Patent Growth in China[1]

With Jie Zhang

3.1 Introduction

The number of patents in China has been exploding in the past three decades. Since 2011, China has become the world's number one in filing patent applications. Breaking the patent counts into invention patents, utility models and designs, this extraordinary growth prevails.[2] According to the National Bureau of Statistics of China, applications for invention patents had increased from 25,236 in 2000 to 293,066 in 2010, with an average annual growth rate of 31.17%. Meanwhile, the utility model (design) patents applications had also risen steadily with a growth rate of 19.86% (24.73%). If different types of patents represent distinct forms of innovation, patent heterogeneity should be important for understanding the driving forces behind China's patent surge as well as its policy implications.

Firms make the patenting decision by analyzing its costs and benefits. In principle, given the supply of new ideas, anything that affects the costs or benefits of patenting can influence the patenting outcome. Different ideas represent various types of innovation. As pointed out by Nemlioglu and Mallick (2017), different

[2] China National Intellectual Property Administration (CNIPA) classifies the patents into three categories. See detailed explanation on this classification in footnote 2.

types of innovation may benefit firms unequally. To distinguish ideas by their novelty and applicability, CNIPA classifies the patents into three categories–invention, utility models, and designs.[3] These three types of patents vary greatly in the length of examination period, protection period as well as requirements for being granted. These differences presumably affect the net benefits of patenting, which further influence firms' incentives for patenting.

Using a novel combined database of Chinese manufacturing firms, this paper aims to deepen the understanding on Chinese patents growth by explicitly considering different types of patents separately. Unlike existing studies, we show that the patent heterogeneity is important in analyzing the patent surge in China. We apply count data models to deal with the problem of over-dispersion and excessive zeros in the patent counts data. Our study documents that factors explaining the patenting growth vary across different types of patents. The empirical results robustly show that R&D investment is one of the most important explanatory factors for all types of patents, but the marginal effect of R&D differs for different types of patents. Contrasting with Hu and Jefferson (2009), we find that foreign direct investment (FDI) only helps explain the creation of utility model and design patents, but not invention patents. More interestingly, different from Li (2012), our study shows that patent subsidy only has positive impact on the patents applications for designs. These results suggest the non-innovation motives are important in explaining the patent applications by firms, but their importance depends on the type of patents. This also implies that certain policies targeted at promoting patenting activities may distort firms' incentives and induce low-quality patents.

Our study relates to several strands of literature. First, it is closely related to the studies on patent surge in China and other countries. To the best of our knowledge, Hu and Jefferson (2009) is the first study documents and analyzes China's patent surge. Using a firm-level dataset that contains invention patents

[3] In China's patent law, invention is referred to the new technical solution proposed for the product, method or related improvement; the utility model refers to a new technical solution suitable for practical use proposed for shape, construction or their combination. According to Article 22 of the Patent Law of the P.R.C.: any invention or utility model for which patent right may be granted must possess novelty, inventiveness and practical applicability. In comparison, the requirement for the approving of design patents is in Article 24 of the Patent Law of the P.R.C as "...... must not be identical with or similar to any design which, before the date of filing, has been publicly disclosed in publications in the country or abroad or has been publicly used in the country, and must not collide with any prior legal rights obtained by any other person."

statistics on large and medium sized industrial enterprises, they show that R&D only explains a fraction of the explosive growth of invention patents. They find that FDI, amendments to the patent law in 2000 and ownership reform have fostered Chinese firms to file more applications for invention patents. In addition to these factors, the stimulating effect of patent subsidy programs initiated by Chinese provincial governments is also documented by Li (2012) and Dang and Motohashi (2015). A recent study by Hu et al. (2017) shows that R&D has become less important in explaining the patenting applications. They also document a weaker correlation between patents and labor productivity. Put together, these studies suggest that the patent growth in China is not only driven by the intensification of R&D but also by other non-innovation motives. Studies on the patent surge in U.S. and Japan indicate that the impact of strengthened IPR protection on patenting is limited. Kortum and Lerner (1999) find that the jump in U.S. patenting between 1985 and 1995 is mainly spurred by the shift in the management of research towards more applied activities but not by the seemingly pro-patent legislative changes in the 1980s. Similarly, Sakakibara and Branstetter (2001) examine the impact of the 1988 Japanese patent law reforms, and also find no evidence supporting that the expanding of patent protection increased the R&D spending or patents.

Second, this study is associated with the literature on the technological effects of FDI. FDI can influence domestic firms through positive agglomeration effects or negative competition effects (Aitken and Harrison, 1999). Since the China's open policy initiated in the 1980s, FDI has played an important role in stimulating China's economic growth. The technological spillovers from FDI, however, remains unclear. This is probably because institutional factors such as the protection of intellectual property rights affect the magnitude of FDI spillovers (Bournakis, Christopoulos, and Mallick, 2018). Using a provincial dataset from 1995 to 2000, Cheung and Ping (2004) find positive impact of FDI on the number of (all types of) domestic patent applications in China. Using panel data analysis on Chinese high-tech industries, Liu and Buck (2007) find the sources of foreign technology spillovers and absorptive ability jointly determine the R&D performance of domestic firms. Nevertheless, Chen, Wang, and Singh (2018) show the domestic private investment has become the dominant contributor to China's technological progress. They notice that the state-owned investment and FDI actually reduce the impact of domestic private investment on stimulating technological advancement. A more comprehensive evaluation of the FDI spillovers by Lu et al. (2017) reveals a negative impact of horizontal FDI, i.e., FDI in the same industry, upon the productivity by Chinese domestic firms. They also find no significant impact of FDI on spurring new products. We also find that FDI has no significant impact on the filings of invention patents, suggesting that the technology spillovers from FDI is limited. Moreover, in our study FDI is found to have significant and positive effects on the patenting for utility models and designs. This implies that firms may employ the patenting for low-quality ideas as a strategic tool to preempt competition from foreign firms. Policies aiming to promote domestic technological progress through attracting FDI may have unintended consequences by inducing firms to produce low-quality patents.

Lastly, our study connects to the literature on the effectiveness of patent-related fees in screening patent quality. Patent fees are an essential element in the design of patent system. A large body of literature has discussed the use of fees as a policy tool to weed out low-quality patents (see Caillaud and Duchêne, 2011; De Rassenfosse and Jaffe, 2018; Gans et al., 2004; Schankerman and Pakes, 1986; Scotchmer, 1999). Our study fits into this strand of literature by focusing on reductions in patenting application fees and examination fees caused by provincial innovation subsidy programs. The empirical results suggest that the decrease in patenting fees induces more design patents. As we mentioned earlier, design patents are of the lowest quality among all types of patents. In this sense, the result suggests that maintaining certain level of patent fees is necessary for screening out low-quality patents. Moreover, this may also reflect that the impact of patenting subsidy on stimulating the firm's innovation is limited. This is probably because patenting fees are small relative to the expected return from patents granted for inventions and utility models.

This paper contributes to the existing literature in several aspects. First, this paper analyzes the patent surge in China by explicitly considering three types of patents separately. We evaluate a set of factors that may affect the patenting outcome for different types of patents in China. This enables us to detect the potentially different driving forces for different categories of patent that represent different forms of innovation, thus providing a more complete explanation of

Chinese patents growth. Second, this study also has important implications for innovation policies. We find that R&D investment, FDI, and patent subsidy play different roles in spurring different types of patents. For example, if patent subsidy is only effective for stimulating low-quality patents, subsidizing on the patenting fees may cause a surge in low-quality patents that harm innovation incentives (Barton, 2000; De Rassenfosse and Jaffe, 2018). Finally, this study also has general implications for researches using patents to measure innovation activities. In addition to R&D investment, other factors may also affect the firm's patenting choice. In this case, using patenting as the measure of innovation regardless of the institutional setting can be misleading. Moreover, innovation can take place in different forms. Different innovation outcome have different market value, using aggregate measures such as R&D investment or the total number of patents disregard the quality of innovation.

The rest of this paper is organized as follows. We introduce the data used in this paper in Section 2. In Section 3, we display the descriptive statistics to motivate the formal econometric analysis on the driving forces behind patents. Section 4 shows the results in the order of the sophistication of the econometric models. Section 5 deals with the potential endogeneity problem. In Section 6 we conclude by discussing the empirical results and relevant policy implications.

3.2 Data

3.2.1 Data sources

This paper uses three databases. The first is a database of Chinese manufacturing firms from 2001 to 2007 compiled by China's National Bureau of Statistics (NBS). This dataset is widely used in economic studies focusing on China (see, for example, Hsieh and Klenow, 2009; Song et al., 2011; Chen et al., 2017). It includes SOEs (State Owned Enterprises) and non-SOEs with annual sales no less than five million *Renminbi* (equivalent to about $700,000). These firms account for 98% of China's total manufacturing exports. The dataset includes more than 100 financial variables listed in the major accounting sheets of all these firms. In particular, it contains information on a firm's annual R&D expenditures.[4]

This study also uses a patents database provided by the CNIPA. It contains information on patent applications that are submitted by firms in mainland China. For each patent the database has information on its type (invention, utility model, or design), owner, application time, certification time, agent of application, abstract, location, and expiration time. This information essentially allows the researcher to track the entire life of patents from 1985 to 2012. But it should be noted that we have no information on patent citations, which makes it difficult to measure the patents quality directly.[5] Different from existing literature, we deal with different patents separately by assuming independence between different types of patents.[6] This allows us to identify different driving forces behind the surge in different kinds of patents. For the purpose of this study, we merge this database with data on Chinese manufacturing firms. The merged dataset contains the information of aforementioned two datasets. In Panel A of Table 1, we report the ratio of the number of patents applications of the merged dataset to the total number patent applications in mainland China. As we can see, the percentage of the total number of patents that are merged to the dataset is increasing for invention patents and utility model patents, decreasing for design patents. This implies that firms have played a more and more important role in producing high-quality patents in our sample, which adds to the importance of this study in understanding the long-term economic growth driven by Chinese firms. Since our dataset only covers around 10% of the total patent applications in China during 2001 to 2007, we have to be conservative should the results be generalized to the overall analysis of China's patent surge. Other entities such as research institutes and universities have also contributed to the patent growth in China (Li, 2012). Another concern is on the efficiency of the matching between two datasets. In the last row of Panel A in Table 3.1, we show the percentage of the total number of invention patents in the merged dataset to the figure in the China Statistical Yearbook on Science and

[4]R&D expenditures are only available for observations no later than 2001, which restricts the time span of the study to be from 2001 to 2007.

[5]Dang and Motohashi (2015) propose to use the 'knowledge width' of each patent as a measure of its quality. This methodology uses the number of nouns in claims to quantify the claim scope; a wider scope of claim represents better patent quality.

[6]Our results are robust if we assume certain correlation between the equation of different types of patents.

Table 3.1: Summary statistics of patents in the merged data

Panel A: Number and percentage of patents in the merged dataset							
year	2001	2002	2003	2004	2005	2006	2007
invention	1982	4462	5333	7993	10100	17033	19750
(%)	6.6	11.2	9.4	12.2	10.8	13.9	12.9
utility model	4202	5649	7496	7798	10720	15324	18212
(%)	5.3	6.1	7.0	7.0	7.8	9.6	10.1
design	6316	8838	9131	10326	12665	15393	16425
(%)	11.2	12.0	10.5	10.2	8.4	8.2	6.5
efficiency (%)	57.1	81.3	96.4	87.2	57.6	67.3	55.7
Panel B: Trend of average number of patent applications							
year	2001	2002	2003	2004	2005	2006	2007
invention	0.016	0.034	0.038	0.072	0.07	0.095	0.117
utility model	0.035	0.043	0.053	0.071	0.075	0.086	0.108
design	0.052	0.068	0.065	0.094	0.088	0.086	0.097

Panel C: R&D and patent application: discrete choices								
	invention		utility model		design		all types	
	No	Yes	No	Yes	No	Yes	No	Yes
$rd_t = 0$	853,150	4,249	848,283	9,116	850,982	6,417	841,760	15,639
$rd_t > 0$	130,449	6,798	126,612	10,635	131,232	6,015	120,631	16,616
$rd_{t-1} = 0$	606,192	3,853	602,412	7,633	604,885	5,160	597,048	12,997
$rd_{t-1} > 0$	99,390	5,652	96,477	8,565	100,312	4,730	91,797	13,245

Note: 'efficiency' in Panel A refers the ratio of number of invention patents in the merged dataset to the published figure in China Statistical Yearbook on Science and Technology 2001-2007.

Technology. We find this ratio varies across years, with 55.57% in 2007 and 96.35% in 2003. We tend to believe that the merged dataset is representative enough for the purpose of this study.

The last dataset this study employs is the information on provincial patent subsidies from 2001-2007. This database is constructed from official documents released on the websites of the provincial intellectual property offices. For each type of patents, the patent subsidy policy is classified into five categories based on various fees and statuses related to the application process, which include reductions in application fees, examination fees, agency costs, and annual fees, as well as grant-contingent rewards after the approving of the application. For each subsidy variable, the outcome can be defined according to one of the three possible states: no subsidy, partial subsidy, and complete subsidy; they are exclusive to each other. Dang and Motohashi (2015) measure the intensity of subsidy by assigning a larger value to complete subsidy than to partial subsidy. To reduce the measurement error caused by almost arbitrarily assigning values for the policy variables, we define the subsidy variable as a dummy variable which is equal to 1 for either partial subsidy or complete subsidy happens and 0 otherwise. This approach also rules out the potential differences between different sub-classes of patent subsidies imposed on different stages of patenting.[7] This full database is reported in Table A1 in the appendix. The final database includes the starting year of the implementation of patent subsidy in China mainland provinces from 2001 to 2007.

3.2.2 Data features

In this subsection, we present some descriptive statistics to motivate the formal econometric analysis in subsequent sections. In general, the preliminary description of the dataset stresses the importance of patent types in investigating the driving forces behind China's patents surge, especially for policies aimed at improving the innovative ability of Chinese firms.

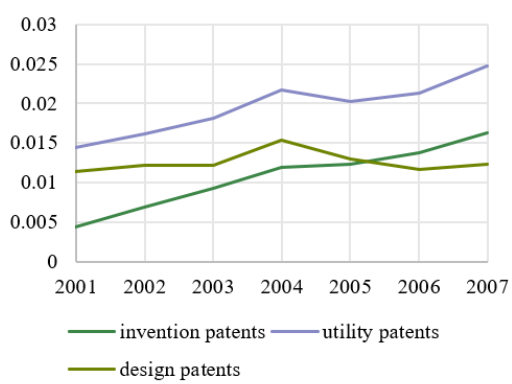
3.2.2.1 Extensive and intensive margins of patent applications

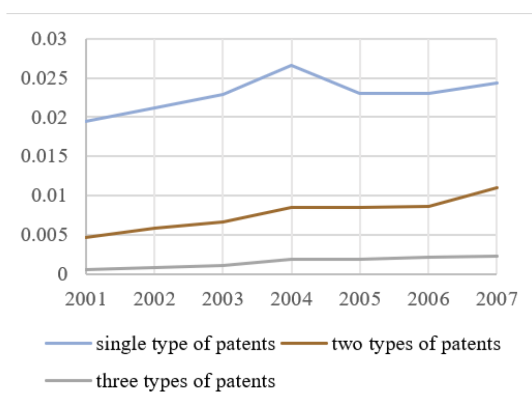
How active are Chinese firms actually in applying for patents? Not surprisingly, a great majority of Chinese firms have never submitted any patent applications. A large fraction of zero-patent counts is an important feature of our data; we will take this into consideration when specifying the econometric models. The average percentage of firms filing patents applications are 1.11%, 1.25%, 1.99% for invention, design, and utility model patents, respectively. It is worth noting that the number of firms that produce patents is much lower than those have positive R&D expenditures. In our data, 11% of the entire observations are actively investing in R&D, which implies that R&D will not be fully transformed into patent ideas. This confirms that patenting is just one mechanism through which firms protect their profits due to innovation (Cohen et al., 2000).

[7] These include reductions in the fees associated with the application, examination, granting, and maintenance of patents.

Although on average Chinese firms are not very active in applying for patents, the percentage of firms applying for invention and utility model patents is in a steady growing trend during our sample period. In Panel A of Figure 1, we plot the trends of patent applications. It shows clearly that the percentage of firms who are applicants for invention patents had reached 1.6% in 2007, almost 3 times larger than it was in 2001. Applications for utility model patents displayed a similar trend; the percentage increased from 1.45% in 2001 to 2.48% in 2007. In contrast, the percentage for active design patents applicants is relatively stable, hovering around 1.2%. In 2006 the percentage of firms applying for invention patents had exceeded that number for design patents. This tells us that firms had become more active in generating invention and utility model patents. As we have mentioned, invention patents and utility model patents are of higher quality than design patents. The evolving patterns of extensive margin of patent applications show that more and more Chinese firms are applying for high-quality patents. Hu et al. (2017) also find that most of China's patenting growth is due to the expansion at the extensive margin during 2007 and 2011.

Figure 3.1: Trends of the number of patent applications





Note: the vertical axis is the ratio of firms that produces patents (for a certain type) to the total number of patents.

We also note that many firms apply for more than one type of patents. To provide a more complete picture of the change in Chinese firm's patent applications, we group the applicants into three cases–single-type patent applicants, two-type patent applicants, and three-type patent applicants (see Panel B of Figure 3.1). It is clear to see a steady growing pattern for all three cases. In particular, the percentage for two-type patent applicants has increased the most, three-type patent applicants the least. This indicates that firms are expanding the variety of patents.

After exploring the extensive margin of the patent application, we turn to describe the characteristics of average patent applications in the dataset. In Panel B of Table 1, we show the evolution of patent intensity defined as the average number of patent applications per firm between 2001 and 2007. As it shows, the average number of invention patents had increased the most, climbing from .016 up to .117. In 2002 and 2004, the increase is around twofold. In comparison, the trend of utility model patents and design patents are smoother. The average number of design patents even exhibited a decreasing trend during 2004-2006, though it bounded back to .097 in 2007.

3.2.2.2 R&D and patent applications

R&D measures the innovation motives for patenting. The significant positive relationship between R&D and patents has been well documented in many studies (Griliches, 1979, 1981; Hausman et al., 1984; Hu and Jefferson, 2009; Hu et al., 2017). Motivated by this literature, we first check the simple correlation between R&D activities and the firm's decision to apply for patents for each type of patents, separately. Panel C of Table 1 shows how the contemporaneous and lagged R&D expenditures are associated with the patent application. Interestingly, many firm observations are found to have positive patent applications even in the absence of R&D investment; the pattern is quite similar for either present or lagged R&D activities. We find some weak evidence suggesting that firms undertaking R&D investment file more patent applications for inventions and utility models. In contrast, we find no evidence supporting that more innovative firms file more patent applications for new designs. At least the preliminary statistics show that non-R&D firms file more design patent applications than R&D-active firms.

Our simple statistics have shown that R&D have heterogeneous effects on the firm's behavior of filing different types of patents. In addition, non-R&D incentives may play a role in explaining the filings of patents applications for designs. Disregarding the substantial heterogeneity when investigating the driving forces of the firm's patent application will bias the estimates and generate misleading results.

3.3 Empirical Strategy

In this section, we employ formal econometric methods to analyze the driving forces behind the surge in different types of patents. To save space, we only present two variations of count data models to deal with over-dispersion and excessive zeros in the data.

3.3.1 Over-dispersion and negative binomial models

3.3.1.1 Over-dispersion in the data

We use N_{it} to denote the number of patent applications, the basic specification of Poisson model is to parameterize the counts of patents as a Poisson distribution with mean λ_{it} that is associated with certain firm characteristics:

$$\Pr\left(N_{it} = n_{it} | \boldsymbol{X}_{it}\right) = \frac{e^{-\lambda_{it}} \lambda_{it}^{n_{it}}}{n_{it}!},$$
$$\lambda_{it} = \exp\left(\mathbf{X}_{it}' \boldsymbol{\beta}\right)$$

where $\mathbf{X}_{it}'$ includes interested explanatory variables. In particular, it can be written as

$$\mathbf{X}_{it}' = \left(\log\left(RD_{it}\right), \log\left(RD_{it-1}\right), \boldsymbol{Z}_{it}'\right)$$

where $\log\left(RD_{it}\right)$ is the log of R&D expenditures, and $\log\left(RD_{it-1}\right)$ is the lagged R&D expenditures. $\boldsymbol{Z}_{it}$ is a vector including other important factors documented in the literature, such as foreign direct investment (fdi_{it}) and\or patent subsidy ($psub_{it}$). To account for the industrial specific effects, we also include a industrial dummy variables that is equal to one when the firm belongs to a high-tech industry.[8] Considering that time effects may affect the growth of patents, we also control for the fixed effects. The specification of Poisson model implicitly imposes the conditional mean and variance of N_{it} are the same. When the conditional variance is greater than the conditional mean, the data are over-dispersed. To detect whether there is over-dispersion in the data, we allow the variance-mean ratio to be any positive constant:

[8]Alternatively, we have tried to include a full set of industry dummies to control for potential industry fixed effects; the results remain robust.

$$\mathrm{Var}\left(N_{it}|\boldsymbol{X}_{it}\right) = \sigma^2\mathbb{E}\left(N_{it}|\boldsymbol{X}_{it}\right) = \sigma^2\lambda_{it} \tag{3.1}$$

Then σ^2 can be estimated using the QMLEs of $\boldsymbol{\beta}$ by considering the sample analog. We estimate the variance-mean ratio for the Poisson models. For all models, the estimation results show that $\hat{\sigma}$'s are greater than one, strongly suggesting over-dispersion in the data. Therefore we use alternative specifications to suit our data better.[9]

3.3.1.2 Negative binomial mean-dispersion model

Following the existing literature on count data models, we consider two approaches to deal with the over-dispersion in the data. One is the mean-dispersion model with a common parameter, the other is a model with a parameterized distribution for the unobserved heterogeneity. Below we only discuss briefly about these two methods. Details about these econometric methods can be found in Cameron and Trivedi (2013).

Mean-dispersion model with common parameter. One way of constructing the negative binomial mean-dispersion model is to introduce unobserved heterogeneity in a Poisson model.[10] Let η_{it} be the unobserved error term and assume that $\exp\left(\eta_{it}\right)$ follow a gamma distribution with parameters $(1/\alpha,\, \alpha)$. Thus $\mathbb{E}\left(\exp\left(\eta_{it}\right)\right) = 1$, $\mathrm{Var}\left(\eta_{it}\right) = \alpha$. We further assume that $\exp\left(\eta_{it}\right)$ is independent of $\boldsymbol{X}_{it}$.[11] It can be shown that the conditional distribution of N_{it} on $\boldsymbol{X}_{it}$ is negative binomial, with conditional mean and variance as follows.[12]

$$\mathbb{E}\left(N_{it}|\boldsymbol{X}_{it}\right) = \lambda_{it} \tag{3.2}$$

$$\mathrm{Var}\left(N_{it}|\boldsymbol{X}_{it}\right) = \lambda_{it} + \alpha\lambda_{it}^2 \tag{3.3}$$

α is called the parameter of over-dispersion; the larger α is, the more over-dispersed

[9] To save space, we do not present the detailed results. The full estimation results are available upon request.

[10] The negative binomial mean-dispersion model is also known as the NegBin Iwemodel (Cameron and Trivedi, 2013)

[11] We will return to discuss this assumption when we consider the endogeneity issue of our models.

[12] See Cameron and Trivedi (2013) for details about the derivation of the negative binomial model.

the data are. In particular, when $\alpha = 0$, the negative binomial specification degenerates to be the Poisson model. In this sense, the negative binomial model generalizes the Poisson model to capture the over-dispersion in the data. As is pointed out, under (3.2), for any fixed positive value for α, the coefficient estimates of $\boldsymbol{\beta}$ by maximizing the associated log likelihood function $\mathcal{L}(\boldsymbol{\beta}, \alpha)$ are consistent (Wooldridge, 2010).

Mean-dispersion model with parameterized α.Although the aforementioned negative binomial mean-dispersion model tackles the over-dispersion in the data to some extent, the assumption that α is identical to all observations is too restrictive. To relax this restriction, we consider parameterizing α as follows

$$\ln(\alpha_{it}) = \gamma_0 + \boldsymbol{W}'_{it}\boldsymbol{\theta} + f_o + f_t \tag{3.4}$$

where $\boldsymbol{W}'_{it}$ is a vector containing *age*, *size*, and *htech*. f_o represent the coefficients of ownership dummies; f_t is the coefficient for year dummies. γ_0, $\boldsymbol{\theta}$, f_o, and f_t are parameters to be estimated along with the other model coefficients.

3.3.2 Excessive zeros of patent applications

In the data section, we have shown that most (around 98%) of the firms do not file any patent applications. This poses challenges to the assumption that the outcome of patents follows a Poisson distribution. To fit the data better, we need to model the event of whether a firm creates patents in addition to the Poisson distribution. Lambert (1992) develops the Zero Inflated Poisson (ZIP) model to deal with this situation. Let p_{it} be the probability that a firm refuses to apply for any patents, then $(1 - p_{it})$ becomes the propensity of applying for some patents. To model the discrete choice to patent or not, we specify following logit model:

$$p_{it} = F(\mathbf{W}'_{it}\boldsymbol{\gamma}) = \frac{1}{1 + \exp(-\mathbf{W}'_{it}\boldsymbol{\gamma})} \tag{3.5}$$

Then the log likelihood function for this specification can be written as:

$$L(\boldsymbol{\gamma}, \boldsymbol{\beta}; n_{it}, \mathbf{X}_{it}, \mathbf{W}_{it}) = \sum_{n_{it}=0} \ln\left\{F(\mathbf{W}'_{it}\boldsymbol{\gamma}) + [1 - F(\mathbf{W}'_{it}\boldsymbol{\gamma})]\, e^{-\exp\left(\mathbf{X}'_{it}\boldsymbol{\beta}\right)}\right\}$$

$$+\sum_{n_{it}>0}\left\{\ln\left[1-F\left(\mathbf{W}_{it}'\boldsymbol{\gamma}\right)\right]-\exp\left(\mathbf{X}_{it}'\boldsymbol{\beta}\right)+n_{it}\mathbf{X}_{it}'\boldsymbol{\beta}-\ln\left(n_{it}!\right)\right\} \tag{3.6}$$

The estimate of $(\boldsymbol{\gamma}, \boldsymbol{\beta})$ is obtained by maximizing the above likelihood function (3.6). To account for the over-dispersion problem, we also add an unobserved component to λ_{it} and estimate a Zero Inflated Negative Binomial (ZINB) model.

3.4 Estimation Results

The estimation results of the negative binomial mean-dispersion model are reported in Table 3.2. First, in each group of the models, the estimation results of α indicate strong over-dispersion in the data. Considering this, the negative binomial model, which takes the over-dispersion into account, fits our data better. In the results of negative binomial model, the patent subsidy is more effective for utility model patents and design patents. Also, private firms and foreign firms are found to file more patent applications than state-owned firms for all types of patents.

Note that the productivity of R&D in creating patents differs across types of patents. The invention patents have the largest R&D-patent elasticity both for the current and lagged R&D, while the design patents display the smallest R&D-patent elasticity. Moreover, the coefficient of lagged R&D is smaller than that of the present R&D for all types of patents. However, for utility models and designs, R&D expenditures become less important for the filings of patents when we control for FDI and patent subsidy. Furthermore, FDI is more effective in stimulating the patenting applications for designs than inventions and utility models. Note that these differences found for various types of patents would disappear if we pool all patents together or only consider a single type of patents. Especially, the estimation results would be much less informative since the potential heterogeneous effects are averaged out when we pool all of the three types of patents together, which are shown in Column (1) in Table 3.2.

In Table 3.3 we display the estimation results for the mean-dispersion model with a parameterized α. As we can see from the results, the coefficients of explanatory variables display a pattern similar to results presented in Table 3.2. This shows that previous results are robust to the alternative parameterization of α. Also note that for the equation of $\ln(\alpha)$, the coefficients of *size*, *age*, and *htech* are all negative, implying that big firms, old firms, and firms in high-tech industries display smaller over-dispersion in the data.

In Table 3.4, we present the results of ZIP and ZINB. For different types of patents, we estimate two different models by including different covariates into $\mathbf{W}_{it}$. In subgroup a, we include patent subsidies, firm size, firm age, ownership dummies, and a constant, while in subgroup b FDI and a full set of year dummies are added. Under our specification, because most of the observations are of zero patent applications, the inflate part of the model captures more about the extensive margin of the patents application. The part of Poisson process is associated more with the intensive margin of the patent application. For any variables included in $\mathbf{X}_{it}$, we say there is a strong evidence showing that it explains the patents outcome when its coefficient is significantly positive in the part of negative binomial model.

There is still a lack of strong evidence showing that patent subsidy stimulates firms to file more invention patents. But the coefficients of $\log(RD_{it})$ and $\log(RD_{it-1})$ are positive and significant at 1% significance level for the group of invention patents. More importantly, these coefficients are larger than those in the groups of utility model patents or design patents, which implies R&D plays a more important role in explaining the invention patents. Last but not the least, the effect of FDI on invention patents is positive. This could be either the impact of foreign competition or knowledge spillovers (Aitken and Harrison, 1999; Lu, Tao, and Zhu, 2017). Overall, these results suggest that FDI is not a significant factor in explaining the patenting outcome when conditioning on the firm's R&D investment.

We can see from the middle columns of Table 4 that both patent subsidy and FDI play significant roles in driving up the number of applications for utility model patents. In all estimations, the coefficient of the dummy variable for private firms are significant and positive for the negative binomial part, and negative for the inflate part. This implies private firms are filing more patents for all of the three types of patents. In contrast, there is only evidence showing that foreign firms are filing more design patents.

3.5 Endogeneity Issue

Our empirical results in previous section display some interesting patterns that are consistent with existing studies by Hu and Jefferson (2009) and Li (2012). However, we should be cautious because of the endogeneity issue caused by unobserved idiosyncratic characteristics. In this section, we try to use panel data methods to deal with this concern. We regard the estimation results as a more convincing interpretation of our dataset.

In the specification of negative binomial model, we allow the variance-to-mean ratio to differ across firms and across time by imposing a specific form to the Poisson parameter. However, a shortcoming of the negative binomial specification is it assumes that the unobserved firm-specific heterogeneity is independent of the explanatory variables. To deal with this problem, we follow Hausman et al. (1984) (HHG hereafter) to estimate a fixed-effects negative binomial model. This model allows for arbitrary dependence between the unobserved idiosyncratic characteristics and the explanatory variables while allowing for over-dispersion in the data.[13] An alternative specification of the error term is the random-effects negative binomial model. We omit the details of its specification. Instead, we show results of the Hausman specification test that favor the fixed-effects model. To save space, we only report the estimation results of fixed effects negative binomial model in Table 3.5.

One noteworthy result in Table 3.5 is a great shrinkage in the sample size. Compared to the original sample size in the pooled regression, most of the observations are deleted due to the all-zero outcomes for the dependent variable. We also report the number of observations deleted because of single observation over the sample period. This great loss of information reminds us to be cautious when interpreting the results.

In Table 3.5, the coefficients of $\log(RD_{it})$ and $\log(RD_{it-1})$ are much smaller than estimates reported in Table 3 and Table 4. Recall that we have shown that there is a substantial R&D investment gap between firms with patent applications and those of no patent application. Since the panel data model drops most of

[13]We also tried to employ the results of fixed effects Poisson model. The results, however, show that fixed effects Poisson model provides a poor fitting to the data with the Hausman testing statistic being negative for most of the groups.

the data with zero patent applications, the remaining dataset contains firms that invest relatively more in R&D. As a result, the variations in patents and R&D both become smaller. The coefficient estimates show that the drop in the variation of patents is more significant compared to that in the variation of investment in R&D. For the coefficient of FDI, we find it only drives the filings of utility model patents and design patents. When we look at the coefficient estimates for patent subsidy, the coefficient is only significantly positive for design patents.

3.6 Conclusion

R&D has a long-lasting effect on firm performance (Bournakis and Mallick, 2018). Our empirical results robustly show that R&D has a positive impact on patenting. This is consistent with the findings in studies investigating the R&D-patents relationship (Griliches, 1981; Hausman et al., 1984; Hall et al., 1986). But a simple calculation can show that R&D growth is not sufficient to explain the patenting growth in China. According to the OECD database, China's R&D expenditures had a 256.27% (215.87%) increase from 1999 to 2006 (2000 to 2007). Given the patent-R&D elasticity reported in Table 5, the predicted patenting growth rate should be 5.64% for invention patents, 7.57% for utility model patents, and 9.24% for design patents. In contrast, the number of invention, utility model, and design patents have a 896.47% , 333.41%, and 160.05% increase in the sample period, separately. This reminds us to consider other factors in order to fully explain the patenting growth in China.

To some extent, the empirical results question the perception that foreign firms have stimulated Chinese firms to apply for more inventive patents. Conditional on the firm's R&D investment, FDI has no significant impact on the patenting for inventions. However, FDI has positive and significant effects on utility model and design patents. Note that the coefficient of FDI is a mixture of spillover effects and competition effects. This result implies that the spillover effect is restricted to low-quality ideas. With the reduced costs of innovation, the competition effect from FDI further encourages Chinese firms to employ relatively low-quality patents to take advantage of some loopholes in the the patent law to compete with foreign firms (Hu and Jefferson, 2009). Lu et al. (2017) also find no beneficial spillovers from FDI in China.

We only find that the patent subsidy has positive and significant effects on the patenting of design patents. We attribute this finding to two main reasons. First, note that design patents are of the lowest quality. Generating a design patent application is of costs lower than an invention patent or utility model patent. Firms make patenting decision by comparing its expected payoffs and costs. If the reductions in the patenting fees are negligible compared to the benefits, the firm's patenting decision will not change. As a result, patenting subsidy will increase the low-quality patent applications disproportionately (De Rassenfosse and Jaffe, 2018). Second, Li (2012) argues that patent subsidies are not only effective in encouraging more individuals and universities to apply for invention patents but also are inducing firms to file more applications for invention patents. According to our results, we expect this argument only works for individuals and small firms which are usually more financially constrained than large firms and research institutions. Overall, patent subsidy has only stimulated the creation of low-quality patents (the design patents). This is consistent with the findings by Dang and Motohashi (2015). We also note that the coefficient of firm size is positive and significant for all the three different types of patents. This implies that larger firms are more likely to apply for patents. There is no significant correlation between firm age and the creation of patents; implying that patenting is neutral to firm age.

The empirical results have several implications for policies aiming to promote innovation in developing countries. First, development policies using FDI as the key driver of technological progress need to be reconsidered. FDI may play an important role in spreading relatively low-quality ideas, but relying on FDI to move up to the technological frontier is much less promising. The cutting-edge technology can only be developed through indigenous R&D. Second, patent subsidies increase the low-quality patents disproportionately by decreasing the patenting fees. The surge in low-quality patents may cause the fragmentation of intellectual property rights. Ultimately, the fragmentation will significantly raise the costs of using knowledge and may discourage R&D investment (Heller and Eisenberg, 1998). In addition, the surge in patenting applications may cause the patents examiners to spend less time on each patent and make more mistakes in granting patent rights. This can also lead to low-quality patents. To guarantee the quality standards, reductions in the patent fees should be combined with improvement in governance of patent offices as well as a supply of more professional patent examiners.

This study stresses the importance of patent quality in understanding the patent surge in China. As indicated by the empirical findings, R&D investment is more important in explaining high-quality patents, while FDI and patent subsidy stimulate the filings of patents of lower quality. It is the future work that we aim to reconcile these findings in a coherent theoretical framework.

Table 3.2: Regression results of negative binomial mean-dispersion model with common α

Dependent Variables	Total patents (1)	Invention (2)	Utility model (3)	Design (4)
Independent Variables				
$\log(RD_{it})$	0.103***	0.137***	0.119***	0.074***
	(0.01)	(0.01)	(0.00)	(0.01)
$\log(RD_{it-1}$	0.077***	0.089***	0.084***	0.064***
	(0.01)	(0.01)	(0.00)	(0.02)
$psub_{it}$	0.455***	0.210**	0.334***	0.584***
	(0.05)	(0.07)	(0.06)	(0.09)
FDI_{jt}	3.255***	2.257***	2.903***	4.109***
	(0.17)	(0.34)	(0.13)	(0.30)
$size_{it}$	0.706***	0.560***	0.627***	0.826***
	(0.02)	(0.03)	(0.02)	(0.04)
age_{it}	0.004*	0.00	0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
$htech_{it}$	0.415***	1.077***	0.289***	0.217**
	(0.04)	(0.08)	(0.04)	(0.07)
$private_{it}$	0.642***	0.467***	0.409***	0.887***
	(0.07)	(0.06)	(0.07)	(0.12)
$foreign_{it}$	0.969***	0.675***	0.553***	1.310***
	(0.08)	(0.09)	(0.08)	(0.14)
constant	-6.984***	-7.232***	-7.116***	-9.008***
	(0.15)	(0.18)	(0.16)	(0.27)
year FE	yes	yes	yes	yes
$\ln(\alpha)$	3.653***	3.686***	3.471***	4.853***
	(0.02)	(0.05)	(0.02)	(0.03)
$\log -pl$	-158500.4	-57374.6	-94996.8	-71006.1
χ^2	8026.2	6269.5	10592	2314.4
$\hat{\alpha}$	38.59	39.89	32.16	128.1
# of obs.		706388		

Note: the dispersion parameter α is common to all observations. χ^2 is the chi-square testing statistic under the null hypothesis that a constant-only model does better. log-pl is the log-pseudo likelihood. All standard errors are robust to some kinds of mis-specification recommended by Cameron and Trivedi (2009). $\hat{\alpha}$ is parameter capturing the over-dispersion.

*** 0.1% significance level; ** 1% significance level; * 5% significance level.

Table 3.3: Estimation results of negative binomial mean-dispersion model with α parameterized

Dependent Variables	Total patents (1)	Invention (2)	Utility model (3)	Design (4)
Independent Variables				
$\log(RD_{it}$	0.098***	0.132***	0.112***	0.074***
	(0.01)	(0.01)	(0.00)	(0.01)
$\log(RD_{it})$	0.068***	0.083***	0.080***	0.053***
	(0.01)	(0.01)	(0.00)	(0.01)
$psub_{jt}$	0.376***	0.168*	0.337***	0.417***
	(0.05)	(0.07)	(0.06)	(0.10)
FDI_{jt}	3.164***	2.495***	3.040***	3.264***
	(0.16)	(0.33)	(0.14)	(0.27)
$size_{it}$	0.718***	0.620***	0.656***	0.786***
	(0.02)	(0.02)	(0.02)	(0.03)
age_{it}	0.00	(0.00)	0.00	(0.00)
	(0.00)	(0.00)	(0.00)	(0.00)
$htech_{it}$	0.411***	1.141***	0.297***	0.160*
	(0.04)	(0.07)	(0.05)	(0.06)
$private_{it}$	0.690***	0.465***	0.423***	0.945***
	(0.06)	(0.06)	(0.07)	(0.10)
$foreign_{it}$	0.921***	0.627***	0.527***	1.226***
	(0.07)	(0.10)	(0.08)	(0.11)
year FE	yes	yes	yes	yes
Dependent variable: $\ln(\alpha)$				
$size_{it}$	-0.392***	-0.380***	-0.328***	-0.509***
	(0.01)	(0.03)	(0.02)	(0.02)
age_{it}	-0.011***	-0.006**	-0.014***	(0.00)
	(0.00)	(0.00)	(0.00)	(0.00)
$htech_{it}$	-0.879***	-0.616***	-0.315***	-1.016***
	(0.03)	(0.08)	(0.05)	(0.05)
$private_{it}$	-0.253***	-0.359***	-0.281**	-0.420***
	(0.05)	(0.09)	(0.09)	(0.07)
$foreign_{it}$	0.130*	0.798***	0.00	-0.222**
	(0.06)	(0.10)	(0.10)	(0.08)
year FE	yes	yes	yes	yes
# of obs.	706388			
$\log -pl$	-155354.3	-56215.7	-93913.4	-69304
χ^2	9571.3	6772.2	10421.9	2995.6

Note: α is parameterized as a function of age, size, htech, and ownership and year dummies. χ^2 is the chi-square testing statistic under the null hypothesis that a constant-only model does better. log-pl is the log-pseudo likelihood. All standard errors are robust to some kinds of mis-specification recommended by . $\hat{\alpha}$ is parameter capturing the over-dispersion.
*** 0.1% significance level; ** 1% significance level; * 5% significance level.

Table 3.4: Estimation results of the zero-inflated Poisson and Negative Binomial models

Types	Invention		Utility model		Design	
	Poisson	NB	Poisson	NB	Poisson	NB
$\log(RD_{it})$	0.125***	0.131***	0.030**	0.108***	(0.00)	0.076***
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$\log(RD_{it-1})$	0.02	0.084***	0.02	0.079***	0.00	0.049***
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$psub_{it}$	0.533**	0.27	(0.01)	0.189***	0.363***	0.814***
	(0.19)	(0.14)	(0.05)	(0.06)	(0.06)	(0.08)
FDI_{jt}	4.288***	3.075***	0.888***	0.32	0.22	(0.47)
	(0.43)	(0.45)	(0.15)	(0.26)	(0.17)	(0.27)
$size_{it}$	0.805***	0.268***	0.490***	0.389***	0.452***	0.357***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
age_{it}	-0.019***	(0.00)	-0.010***	-0.014***	-0.009***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$private_{it}$	0.06	0.20	0.358***	0.303**	0.497***	0.732***
	(0.26)	(0.14)	(0.08)	(0.11)	(0.09)	(0.12)
$foreign_{it}$	(0.57)	1.403***	0.354***	0.574***	0.535***	0.969***
	(0.39)	(0.18)	(0.08)	(0.13)	(0.10)	(0.14)
$hitech_{it}$	0.920***	0.578***	0.282**	0.153*	-0.305***	-0.683***
	(0.13)	(0.12)	(0.09)	(0.07)	(0.07)	(0.08)
$\log(\alpha)$	–	2.581***	–	2.669***	–	3.476***
		(0.05)		(0.05)		(0.05)
$\log -pl$	-105770.9	-56429.5	-123183.4	-93710.7	-122782.6	-68700.1
χ^2statistic	255719.7	12490.2	39774.8	10394.1	26176.1	2709.9
Vuong test	20.54	11.62	40.56	13.87	35.71	21.83
# of obs.			706388			

Note: Vuong test is the model specification test on zero-inflated negative binomial model versus standard negative binomial model (Vuong, 1989), with the null hypothesis that the standard negative binomial model fits the data better. Year dummies are include in all specifications. The standard errors are adjusted for the correlation between equations. *** 0.1% significance level; ** 1% significance level; * 5% significance level.

Table 3.5: Estimation results of fixed effects negative binomial model

Dependent Var.	Total patents	Invention	Utility model	Design
	(1)	(2)	(3)	(4)
Independent Var.				
$\log(RD_{it})$	0.030***	0.019***	0.022***	0.025***
	(0.00)	(0.00)	(0.00)	(0.00)
$\log(RD_{it-1})$	0.016***	0.006*	0.011***	0.015***
	(0.00)	(0.00)	(0.00)	(0.00)
$psub_{it}$	0.07	(0.03)	0.09	0.194**
	(0.04)	(0.06)	(0.05)	(0.07)
FDI_{jt}	0.386***	0.22	0.321**	0.928***
	(0.09)	(0.15)	(0.12)	(0.14)
$size_{it}$	0.139***	0.148***	0.095***	0.221***
	(0.01)	(0.02)	(0.01)	(0.02)
age_{it}	0.00	0.001	-0.00	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
year FE	yes	yes	yes	yes
# of obs.	65140	27530	42155	28087
reason I: dropped obs.	73051	73051	73051	73051
reason II:dropped obs.	568197	605807	591182	605250
(groups)	(147510)	(155232)	(152223)	(155127)
$\log -pl$	-55319.2	-16803.1	-30604.3	-21716.8
χ^2	1782.40	1318.70	1088.10	582.60
Hausman test χ^2	14063.63	6130.26	8296.64	3566.26

Note: Hausman test is the specification test under the null hypothesis that random-effects model and fixed-effects model have no systematic difference in coefficients. χ^2 is the chi-square testing statistic under the null hypothesis that a constant-only model does better. $\log -pl$ is the log-pseudo likelihood. Reason I for dropping observations is the single observation over the sample period; reason II is the all-zero outcomes observations. All standard errors are clustered at city level.
*** 0.1% significance level; ** 1% significance level; * 5% significance level.

Appendix A

Appendix to Chapter 1

A.1 Math Appendix

A.1.1 Marginal cost of capital

The firm's optimization problem is

$$\max_{l_{it},k_{it}}\{y_{it}-\omega l_{it}-rk_{it}\} \tag{A.1}$$

$$s.t.\ k_{it}\leq\frac{a_{it}}{1-\theta}+\frac{\theta}{1-\theta}\phi_{it}^{\eta} \tag{A.2}$$

where $y_{it}=\left(\phi_{it}k_{it}^{\alpha}l_{it}^{1-\alpha}\right)^{\frac{1}{\bar{m}}}$ and $\bar{m}=\frac{\sigma}{\sigma-1}$ is the mark up. Let λ_{it} be the Lagrangian multiplier for the capital constraint, the first-order conditions are:

$$\frac{1-\alpha}{\bar{m}}\left(\phi_{it}k_{it}^{\alpha}\right)^{\frac{1}{\bar{m}}}l_{it}^{\frac{1-\alpha}{\bar{m}}-1}=\omega \qquad \Rightarrow\ l_{it}=\frac{(1-\alpha)\,y_{it}}{\bar{m}\omega} \tag{A.3}$$

$$\frac{\alpha}{\bar{m}}\left(\phi_{it}l_{it}^{1-\alpha}\right)^{\frac{1}{\bar{m}}}k_{it}^{\frac{\alpha}{\bar{m}}-1}=r+\delta+\lambda_{it} \qquad \Rightarrow\ k_{it}=\frac{\alpha y_{it}}{\bar{m}\left(\lambda_{it}+r+\delta\right)} \tag{A.4}$$

$$k_{it}=\frac{a_{it}}{1-\theta}+\frac{\theta}{1-\theta}\phi_{it}^{\eta}\ \text{iff}\ \lambda_{it}>0 \tag{A.5}$$

where the last condition is the complementary slackness condition. Using (A.3) and (A.4) I solve for the optimal choice of labor and capital:

$$k_{it} = \frac{1}{\bar{m}^{\sigma}} \left(\frac{1-\alpha}{\omega}\right)^{(1-\alpha)(\sigma-1)} \left(\frac{\alpha}{\lambda_{it}+r+\delta}\right)^{1+\alpha(\sigma-1)} \phi_{it}^{\sigma-1} \tag{A.6}$$

$$l_{it} = \frac{1}{\bar{m}^{\sigma}} \left(\frac{1-\alpha}{\omega}\right)^{\alpha+\sigma(1-\alpha)} \left(\frac{\alpha}{\lambda_{it}+r+\delta}\right)^{\alpha(\sigma-1)} \phi_{it}^{\sigma-1} \tag{A.7}$$

When $\lambda_{it} > 0$, I can use the binding capital constraint and (A.6) to solve for the capital prices:

$$R\left(a_{it},\, \phi_{it}\right) = D \left[\phi_{it} \left(\frac{a_{it}}{1-\theta} + \frac{\theta \phi_{it}^{\eta}}{1-\theta}\right)^{1-\bar{m}}\right]^{\frac{1}{\bar{m}+\alpha-1}} \tag{A.8}$$

where

$$D \equiv \frac{\alpha}{\bar{m}} \left(\frac{1-\alpha}{\bar{m}\omega}\right)^{\frac{1-\alpha}{\bar{m}+\alpha-1}}$$

When $\lambda_{it} = 0$, the capital price is $R\left(a_{it},\, \phi_{it}\right) = r + \delta$.

A.1.2 Investment-cashflow sensitivity

Notice in the model the capital investment-cash flow sensitivity is one when a firm is financially constrained, hence ζ also represents the average investment-cash flow sensitivity, which was introduced by Fazzari et al. (1988) and has been used extensively in the empirical literature in financial economics. See appendix for the discussion on the cash flow-investment sensitivity. When the capital constraint is binding, the capital investment is independent of the cash flow. When the firm is constrained, the capital investment is given by

$$\begin{aligned} k_{it} &= \frac{1}{\bar{m}^{\sigma}} \left(\frac{1-\alpha}{\omega}\right)^{(1-\alpha)(\sigma-1)} \left[\frac{\alpha}{R\left(a_{it},\, \phi_{it}\right)}\right]^{1+\alpha(\sigma-1)} \phi_{it}^{\sigma-1} \\ &\propto \lambda\left(a_{it},\, \phi_{it+1}\right) \end{aligned}$$

It follows that $\epsilon_{it} = \frac{\partial \ln(k_{it})}{\partial \ln(\lambda(a_{it}, \phi_{it}))} = 1$. Let P_c be the fraction of constrained firms, the average cashflow sensitivity is

$$\zeta_t = \frac{1}{N} \sum_i \epsilon_i \times \mathbb{I}(constrained) = P_c \tag{A.9}$$

A.1.3 Static aggregate TFP loss

A.1.3.1 Aggregate TFP

I first show that given the distribution of fundamentals (a_t, ϕ_t), the aggregate TFP can be written as

$$TFPQ_t = \frac{\left[\int_{i \in N} R_{it}^{\alpha(1-\sigma)} \phi_{it}^{\sigma-1} di\right]^{\frac{1}{\sigma-1}+\alpha}}{\left[\int_{i \in N} R_{it}^{\alpha(1-\sigma)-1} \phi_{it}^{\sigma-1} di\right]^{\alpha}} \tag{A.10}$$

By the definition of aggregate TFP, we know

$$TFPQ_t = \frac{Q_t}{K_t^{\alpha} L_t^{1-\alpha}} = \frac{Q_t}{\left(\int_i k_{it} d_i\right)^{\alpha} \left(\int_i l_{it} di\right)^{1-\alpha}} \tag{A.11}$$

Let's first look at the aggregate inputs. Using the optimal decisions of capital and labor, I immediately have

$$K_t = \int_i k_{it} di = \frac{P_t^{\sigma} Q_t}{\bar{m}^{\sigma}} \left(\frac{1-\alpha}{\omega}\right)^{(1-\alpha)(\sigma-1)} \alpha^{1+\alpha(\sigma-1)} \int_i R_{it}^{\alpha(1-\sigma)-1} \phi_{it}^{\sigma-1} di \tag{A.12}$$

$$L_t = \int_i l_{it} di = \frac{P_t^{\sigma} Q_t}{\bar{m}^{\sigma}} \left(\frac{1-\alpha}{\omega}\right)^{\alpha+\sigma(1-\alpha)} \alpha^{\alpha(\sigma-1)} \int_i R_{it}^{\alpha(1-\sigma)} \phi_{it}^{\sigma-1} di \tag{A.13}$$

Moreover, the aggregate industrial output is

$$\begin{aligned} Q_t &= \left(\int q_{it}^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \\ &= \frac{P_t^{\sigma} Q_t}{\bar{m}^{\sigma}} \left[\left(\frac{1-\alpha}{\omega}\right)^{(1-\alpha)(\sigma-1)} \alpha^{1+\alpha(\sigma-1)}\right]^{\alpha} \\ &\quad \left[\left(\frac{1-\alpha}{\omega}\right)^{\alpha+\sigma(1-\alpha)} \alpha^{\alpha(\sigma-1)}\right]^{1-\alpha} \times \left[\int R_{it}^{\alpha(1-\sigma)} \phi_{it}^{\sigma-1} di\right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{A.14}$$

Plugging the expressions of K_t and L_t into (A.11), canceling the aggregate variables $P_t^{\sigma} Q_t$ and other constants, I obtain (A.10).

Now I focus on a specific joint distribution of (a_{it}, ϕ_{it}) and obtain the estimator for aggregate TFP loss. In particular, we assume that the net worth a_{it} and productivity ϕ_{it} follow a joint log normal distribution

$$\begin{bmatrix} \log(a_{it}) \\ \log(\phi_{it}) \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} \mu_a \\ \mu_\phi \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \tilde{\rho}\sigma_a\sigma_\phi \\ \tilde{\rho}\sigma_a\sigma_\phi & \sigma_\phi^2 \end{bmatrix} \right)$$

Let $G(a, \phi)$ be the CDF and $g(a, \phi)$ be the PDF, respectively. Define $u \equiv \log(a)$ and $v \equiv \log(\phi)$, then the density function for (u, v) is

$$h(u, v) = \frac{1}{2\pi\sigma_a\sigma_\phi\sqrt{1-\tilde{\rho}^2}} \exp\left[-\frac{z(u,v)}{2(1-\tilde{\rho}^2)}\right] \tag{A.15}$$

$$\text{where } z = \frac{(u-\mu_a)^2}{\sigma_a^2} - \frac{2\tilde{\rho}(u-\mu_a)(v-\mu_\phi)}{\sigma_a\sigma_\phi} + \frac{(v-\mu_\phi)^2}{\sigma_\phi^2}$$

Applying the change of variables theorem for this bi-variate case, I have

$$g(a, \phi) = \frac{1}{a\phi} h(\log(a), \log(\phi)) \tag{A.16}$$

In addition, I normalize that $P_t^\sigma Q_t = 1$ to simplify our analysis to be on the partial equilibrium. I define a cut-off function $\bar{\phi}(a)$ such that $\left(a, \bar{\phi}(a)\right)$ solves

$$R\left(a, \bar{\phi}(a)\right) = r + \delta \tag{A.17}$$

Correspondingly, I define a function $\bar{v}(u) \equiv \log\left(\bar{\phi}(e^u)\right)$ that characterizes the cut-off function on the space of (u, v). Now I omit the time subscripts for the sake of brevity.

Theorem 1. When the fraction of constrained firms are small, the aggregate TFP can be approximated as

$$TFPQ = N^{\frac{1}{\sigma-1}} \Upsilon_0(\Theta)^{\frac{1}{\sigma-1}} e^{\mu_\phi + \frac{(\sigma-1)\sigma_\phi^2}{2}}$$

Proof. Applying the Law of Large Numbers, I can express the numerator and denominator of $TFPQ$ as

$$\left[\int R_{it}^{\alpha(1-\sigma)} \phi_{it}^{\sigma-1} di\right]^{\frac{1}{\sigma-1}+\alpha}$$

$$= N^{\frac{1}{\sigma-1}+\alpha}\left[\mathbf{E}\left(R_{it}^{\alpha(1-\sigma)}\phi_{it}^{\sigma-1}\right)\right]^{\frac{1}{\sigma-1}+\alpha}$$
$$= N^{\frac{1}{\sigma-1}+\alpha}\left[\int_0^\infty\int_0^\infty R\left(a,\,\phi\right)^{\alpha(1-\sigma)}\phi^{\sigma-1}g\left(a,\,\phi\right)d\phi da\right]^{\frac{1}{\sigma-1}+\alpha}$$
$$\propto\left[\left(r+\delta\right)^{\alpha(1-\sigma)}\int\int_{-\infty}^{\bar{\phi}(a)}\phi^{\sigma-1}dG\left(a,\,\phi\right)\right.$$
$$\left.+\int\int_{\bar{\phi}(a)}^{\infty}\phi^{\sigma-1}R\left(a,\,\phi\right)^{\alpha(1-\sigma)}dG(a,\phi)\right]^{\frac{1}{\sigma-1}+\alpha}\times\left[\int_{i\in N}R_{it}^{\alpha(1-\sigma)-1}\phi_{it}^{\sigma-1}di\right]^{\alpha}$$
$$\propto\left[\left(r+\delta\right)^{\alpha(1-\sigma)-1}\int\int_{-\infty}^{\bar{\phi}(a)}\phi^{\sigma-1}dG\left(a,\,\phi\right)\right.$$
$$\left.+\int\int_{\bar{\phi}(a)}^{\infty}\phi^{\sigma-1}R\left(a,\,\phi\right)^{\alpha(1-\sigma)-1}dG(a,\phi)\right]^{\alpha}$$

Changing the variables to be u and v , the first double integral in the bracket is

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\bar{v}(u)}e^{(\sigma-1)v}g\left(e^u,e^v\right)de^v de^u=\int_{-\infty}^{\infty}\int_{-\infty}^{\bar{v}(u)}e^{(\sigma-1)v}h\left(u,\,v\right)dvdu$$
$$=\int_{-\infty}^{\infty}\int_{-\infty}^{\bar{v}(u)}\frac{1}{2\pi\sigma_a\sigma_\phi\sqrt{1-\tilde{\rho}^2}}$$
$$\times\exp\left(\left(\sigma-1\right)v-\frac{z\left(u,v\right)}{2\left(1-\tilde{\rho}^2\right)}\right)dvdu$$

Integrating from the integral inside, I have

$$\int_{-\infty}^{\bar{v}(u)}\frac{1}{2\pi\sigma_a\sigma_\phi\sqrt{1-\tilde{\rho}^2}}\exp\left(\left(\sigma-1\right)v-\frac{z\left(u,v\right)}{2\left(1-\tilde{\rho}^2\right)}\right)dv$$
$$=\frac{1}{\sqrt{2\pi\left(1-\tilde{\rho}^2\right)}\sigma_a}e^{-\frac{(u-\mu_a)^2}{2\left(1-\tilde{\rho}^2\right)\sigma_a^2}-\frac{\tilde{\rho}\mu_\phi(u-\mu_a)}{\left(1-\tilde{\rho}^2\right)\sigma_a\sigma_\phi}+\frac{\left[\mu_\phi+\tilde{\rho}\sigma_\phi(u-\mu_a)/\sigma_a\right]^2-\mu_\phi^2}{2\left(1-\tilde{\rho}^2\right)\sigma_\phi^2}}$$
$$\times\int_{-\infty}^{\bar{v}(u)}\frac{1}{\sqrt{2\pi}\sigma_\phi}e^{-\frac{\left[v-\left(\mu_\phi+\tilde{\rho}\sigma_\phi(u-\mu_a)/\sigma_a\right)\right]^2-2(\sigma-1)\left(1-\tilde{\rho}^2\right)\sigma_\phi^2v}{2\left(1-\tilde{\rho}^2\right)\sigma_\phi^2}}dv$$
$$=\frac{1}{\sqrt{2\pi}\sigma_a}e^{-\frac{(u-\mu_a)^2}{2\sigma_a^2}+(\sigma-1)\left[\frac{\tilde{\rho}\sigma_\phi(u-\mu_a)}{\sigma_a}+\mu_\phi\right]+\frac{\left(1-\tilde{\rho}^2\right)(\sigma-1)^2\sigma_\phi^2}{2}}\times$$
$$\int_{-\infty}^{\bar{v}(u)}\frac{1}{\sqrt{2\pi\left(1-\tilde{\rho}^2\right)}\sigma_\phi}e^{-\frac{\left[v-\left((\sigma-1)\left(1-\tilde{\rho}^2\right)\sigma_\phi^2+\tilde{\rho}(u-\mu_a)\frac{\sigma_\phi}{\sigma_a}+\mu_\phi\right)\right]^2}{2\left(1-\tilde{\rho}^2\right)\sigma_\phi^2}}dv$$
$$=\frac{1}{\sqrt{2\pi}\sigma_a}e^{-\frac{(u-\mu_a)^2}{2\sigma_a^2}+(\sigma-1)\left[\frac{\tilde{\rho}\sigma_\phi(u-\mu_a)}{\sigma_a}+\mu_\phi\right]+\frac{\left(1-\tilde{\rho}^2\right)(\sigma-1)^2\sigma_\phi^2}{2}}\Phi\left(\frac{\bar{v}\left(u\right)-\tilde{v}_0\left(u\right)}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}\right)$$

where $\Phi(\cdot)$ is the CDF of standard normal distribution and

$$\tilde{v}_0(u) \equiv (\sigma-1)\left(1-\tilde{\rho}^2\right)\sigma_\phi^2 + \tilde{\rho}(u-\mu_a)\frac{\sigma_\phi}{\sigma_a} + \mu_\phi.$$

This implies that

$$\begin{aligned}
&\int_{-\infty}^{\infty}\int_{-\infty}^{\bar{v}(u)} e^{(\sigma-1)v} h(u,\, v)\, dvdu \\
&= e^{\frac{\left(1-\tilde{\rho}^2\right)(\sigma-1)^2\sigma_\phi^2}{2}+(\sigma-1)\mu_\phi} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_a} e^{-\frac{(u-\mu_a)^2}{2\sigma_a^2}+(\sigma-1)\frac{\tilde{\rho}\sigma_\phi(u-\mu_a)}{\sigma_a}} \Phi\left(\frac{\bar{v}(u)-\tilde{v}_0(u)}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}\right) du \\
&= e^{\frac{(\sigma-1)^2\sigma_\phi^2}{2}+(\sigma-1)\mu_\phi} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \Phi\left(\frac{\bar{v}(u_0(y))-\tilde{v}_0(u_0(y))}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}\right) dy
\end{aligned}$$

Define that

$$\Upsilon_0(\Theta) \equiv \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} \Phi\left(\frac{\bar{v}(u_0(y))-\tilde{v}_0(u_0(y))}{\sqrt{1-\tilde{\rho}^2}\sigma_\phi}\right) dy,$$

where $\Theta \equiv (\mu_a,\, \sigma_a,\, \tilde{\rho})$ and

$$y = \frac{u-\mu_a-(\sigma-1)\sigma_a\sigma_\phi}{\sigma_a} \Leftrightarrow u_0(y) = \sigma_a y + \mu_a + (\sigma-1)\sigma_a\sigma_\phi$$

is used to change the integrand. For the numerator, the second double integral in the bracket is

$$\begin{aligned}
\int\int_{\bar{\phi}(a)}^{\infty} \phi^{\sigma-1} R(a,\, \phi)^{\alpha(1-\sigma)}\, d\phi da &= \int\int_{\bar{v}(u)}^{\infty} e^{(\sigma-1)v} R(e^u,\, e^v)^{\alpha(1-\sigma)}\, g(e^u, e^v)\, de^u de^v \\
&= \int_{-\infty}^{\infty}\int_{-\infty}^{\bar{v}(u)} R(e^u,\, e^v)^{\alpha(1-\sigma)}\, e^{(\sigma-1)v} dH(u,v) \\
&= D_t^{\alpha(1-\sigma)} \int\int_{-\infty}^{\bar{v}(u)} \lambda(e^u,\, e^v)^{\frac{\alpha}{\alpha+\bar{m}-1}}\, e^{\frac{v}{\bar{m}+\alpha-1}} dH(u,v)
\end{aligned}$$

For the denominator, the second double integral in the bracket is

$$\int\int_{\bar{\phi}(a)}^{\infty} \phi^{\sigma-1} R(a,\, \phi)^{\alpha(1-\sigma)}\, d\phi da = D_t^{\alpha(1-\sigma)-1} \int\int_{-\infty}^{\bar{v}(u)} \lambda(e^u, e^v)\, dH(u,v) \quad \text{(A.18)}$$

Therefore I can write down the aggregate TFP as

$$TFPQ \propto \Upsilon_0 \left(\Theta\right)^{\frac{1}{\sigma-1}} e^{\mu_\phi + \frac{(\sigma-1)\sigma_\phi^2}{2}} \frac{\left[1 + \left(\frac{D_t}{r+\delta}\right)^{\alpha(1-\sigma)} \Upsilon_1 \left(\Theta\right)\right]^{\alpha+\frac{1}{\sigma-1}}}{\left[1 + \left(\frac{D_t}{r+\delta}\right)^{\alpha(1-\sigma)} \Upsilon_2 \left(\Theta\right)\right]^{\alpha}} \tag{A.19}$$

where

$$\Upsilon_1 \left(\Theta\right) \equiv \frac{\int \int_{-\infty}^{\bar{v}(u)} \lambda \left(e^u, e^v\right)^{\frac{\alpha}{\alpha+\bar{m}-1}} e^{\frac{v}{\bar{m}+\alpha-1}} dH \left(u, v\right)}{\Upsilon_0 \left(\Theta\right) e^{(\sigma-1)\mu_\phi + \frac{(\sigma-1)^2\sigma_\phi^2}{2}}}$$

$$\Upsilon_2 \left(\Theta\right) \equiv \frac{\int \int_{-\infty}^{\bar{v}(u)} \lambda \left(e^u, e^v\right) dH \left(u, v\right)}{\Upsilon_0 \left(\Theta\right) e^{(\sigma-1)\mu_\phi + \frac{(\sigma-1)^2\sigma_\phi^2}{2}}}$$

when $\Upsilon_1$and Υ_2 are close to zero, I obtain that

$$TFPQ = N^{\frac{1}{\sigma-1}} \Upsilon_0 \left(\Theta\right)^{\frac{1}{\sigma-1}} e^{\mu_\phi + \frac{(\sigma-1)\sigma_\phi^2}{2}}$$

$\square$

A.1.3.2 Characterization of aggregate TFP loss

The efficient aggregate TFP is given by

$$\begin{aligned} TFPQ^e &= \left(\int_i \phi_{it}^{\sigma-1} di\right)^{\frac{1}{\sigma-1}} \\ &= N^{\frac{1}{\sigma-1}} \left(\mathbf{E}\left(\phi_t^{\sigma-1}\right)\right)^{\frac{1}{\sigma-1}} \end{aligned}$$

Because ϕ_t has a log-normal distribution with mean μ_ϕ and variance σ_ϕ, I have

$$TFPQ^e = N^{\frac{1}{\sigma-1}} e^{(\sigma-1)\mu_\phi + \frac{(\sigma-1)}{2}\sigma_\phi^2} \tag{A.20}$$

Consider the case that $\Upsilon_1 \left(\Theta\right)$ and $\Upsilon_2 \left(\Theta\right)$ are close to zero, I can calculate the log of TFP loss as

$$\begin{aligned} TFP\, loss &= 1 - \frac{TFPQ}{TFPQ^e} \\ &= 1 - \Upsilon_0 \left(\Theta\right)^{\frac{1}{\sigma-1}} \end{aligned}$$

Theorem 2. When $\bar{v}(u)$ is an increasing (decreasing) function of u, the aggregate TFP loss is decreasing (increasing) in μ_a. The aggregate TFP loss is and increasing in μ_ϕ.

Proof. First, note that I can write $\tilde{v}_0(u_0(y))$ as

$$\tilde{v}_0(u_0(y)) = \tilde{\rho}\sigma_a y + (\sigma - 1)\left(1 - \tilde{\rho}^2\right)\sigma_\phi^2 + \tilde{\rho}(\sigma - 1)\sigma_\phi^2 + \mu_\phi,$$

which is independent of μ_a. The derivative of $\Upsilon_0(\Theta)$ with respect to μ_a is

$$\begin{aligned}\frac{\partial \Upsilon_0(\Theta)}{\partial \mu_a} &= \int \frac{1}{\sqrt{2\pi}\sigma_a} e^{-\frac{y^2}{2}} \Phi' \frac{\bar{v}'(u_0(y))\sigma_a}{\sqrt{1 - \tilde{\rho}^2}\sigma_\phi} dy \lesseqqgtr 0 \\ &\Leftrightarrow \bar{v}'(u_0(y)) \lesseqqgtr 0\end{aligned}$$

Following a similar logic, I know that

$$\frac{\partial \Upsilon_0(\Theta)}{\partial \mu_\phi} = \int \frac{1}{\sqrt{2\pi}\sigma_a} e^{-\frac{y^2}{2}} \Phi' \frac{-1}{\sqrt{1 - \tilde{\rho}^2}\sigma_\phi} dy < 0$$

□

A.2 Theory Appendix

Here I provide a micro foundation for the functional form chosen in our benchmark model. Let $V^D(a, \phi)$ be the value function when the firm defaults and $V^N(a, \phi)$ be the value function when the firm does not default. When not defaulting, the value function is given by

$$V^N(a, \phi) = V(a, \phi) = \max_{b', k', x} \left\{ \frac{c^{1-\epsilon}}{1 - \epsilon} + \beta \mathbf{E} V(a', \phi') \right\} \tag{A.21}$$

subject to the constraint:

$$c + k' + (1 + r)b + \mathbb{I}(x)f + \frac{d}{2}x^2 = y - \omega l + (1 - \delta)k + b'$$

where b is the amount of debt in the next period, and k' is the physical capital in the next period. By definition, I always have $a = k - b$. Because of limited enforcement of contracts, a firm can default on a fraction of the face value of current debt. Therefore the firm only needs to pay $(1+r-\mu_0)b$ to the bank. The cost of defaulting is a fraction of collateral used when borrowing from the bank: $\mu_1(1-\delta)k+\mu_2\Psi(\phi)$. In other words, the bank can seize a fraction of the capital and the value of intangible assets when the firm defaults. The firms are assumed to be only defaulting for one period and have access to the financial market next period. This implies that $V^D(a,\phi)$ can be expressed as:

$$V^D(a,\phi)=\max_{b',k',x}\left\{\frac{c^{1-\epsilon}}{1-\epsilon}+\beta\mathbf{E}V(a',\phi')\right\} \tag{A.22}$$

subject to the constraint:

$$c+k'+(1+r-\mu_0)b+\mu_1(1-\delta)k+\mu_2\Psi(\phi)+\mathbb{I}(x)f+\frac{d}{2}x^2=y-\omega l+(1-\delta)k+b'$$

The condition for an equilibrium in which no firm defaults is

$$\begin{aligned} & V^D(a,\phi)\leq V^N(a,\phi) \\ \Rightarrow\ & (1+r)b\leq(1+r-\mu_0)b+\mu_1(1-\delta)k+\mu_2\Psi(\phi) \end{aligned}$$

This immediately implies that

$$b\leq\frac{\mu_1}{\mu_0}k+\frac{\mu_2}{\mu_0}\Psi(\phi) \tag{A.23}$$

Lastly, I determine the functional form of the value of intangible asset as follows. I assume that the productivity can be decomposed into organization capital ($\phi^{1-\nu}$) and intangible assets (ϕ^{ν}), where $1>\nu>0$. The organization capital is not pledgeable while the intangible assets can be used as a collateral when the firm borrows from the financial institutions. The intangible assets can only be used by a potential manufacturer with organization capital greater than $\phi^{1-\nu}$ and generate profits of $\chi\phi^{\sigma-1}$. Furthermore, the distribution of the organization capital follows a Pareto distribution with lower bound $\underline{\phi}$ ($\phi^{1-\nu}>\underline{\phi}$) and shape parameter m. Therefore, with probability $(\phi^{1-\nu}/\underline{\phi})^{-m}$. This implies that the value of pledged intangible asset is

$$\Psi(\phi)=\chi\underline{\phi}^{m}\phi^{\sigma-m(1-\nu)-1} \tag{A.24}$$

Define $\eta \equiv m(\nu - 1) + \sigma - 1$ and $\theta \equiv \mu_1/\mu_0$. Moreover, if I impose that $\chi \underline{\phi}^m = \mu_1$, I obtain the specification used in our benchmark model. Note that in addition to financial friction, m also captures the efficiency of the market for intellectual property rights including patents and trademarks. A smaller m means that banks can sell the pledged intellectual property rights to a productive potential buyer more easily.

A.3 Characterization of the Steady State

In this section, I provide a characterization of the steady state of the model. According to our aggregation of the economy, aggregate outcomes are determined by the joint distribution of the state variables (a_t, ϕ_t). Note that in the endogenous productivity model, the evolution of net worth and productivity is summarized by a non-linear first-order stochastic differential equation:

$$a_{t+1} = a'(a_t, \phi_t) \tag{A.25}$$

$$\phi_{t+1} = \rho\phi_t + \gamma \ln(x(a_t, \phi_t) + 1) + \xi_{t+1}, \tag{A.26}$$

where $a'(a_t, \phi_t)$ is the decision rule of the accumulation of future net worth, $x(a_t, \phi_t)$ is the optimal choice of R&D investment. This *non-linear vector auto-regressive model* can be approximated by following first-order linear vector auto-regressive model:

$$\begin{bmatrix} a_{t+1} \\ \phi_{t+1} \end{bmatrix} = \begin{bmatrix} a^{(0)} \\ \phi^{(0)} \end{bmatrix} + \underbrace{\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}}_{B} \begin{bmatrix} a_t \\ \phi_t \end{bmatrix} + \begin{bmatrix} 0 \\ \xi_{t+1} \end{bmatrix} \tag{A.27}$$

where

$$\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} = \begin{bmatrix} \frac{\partial a'(a,\phi)}{\partial a} & \frac{\partial a'(a,\phi)}{\partial \phi} \\ \gamma\frac{\partial \ln(x(a,\phi)+1)}{\partial a} & \rho + \gamma\frac{\partial \ln(x(a,\phi)+1)}{\partial \phi} \end{bmatrix}_{a=\mathbf{E}(a),\phi=\mathbf{E}(\phi)}$$

The necessary and sufficient condition ensuring the weak stationarity of this VAR(1) model is the eigenvalues of B has to be smaller than 1 in modulus.

A.4 Data

A.4.1 Panel data of Chinese manufacturing firms

In this subsection, I provide the detailed information on the construction of variables used in the paper.

Net Worth a_{it}: Difference between book value of total assets and total liabilities and deflated by industry output price deflators.

(Net) Debt b_{it}: Book value of current liabilities minus cash holdings and deflated this difference with the industry output price deflators. This is a short-term measure of the debt; the model has no maturity choice.

Capital Stock k_{it}. Book value of fixed assets and deflated with the price of investment goods.[1]

Wage Bill ω_{it}. Book value of sum of salary and payments for labor insurance and other benefits including health insurance, pension insurance, and other insurance.

Labor Input l_{it}. The firm's wage bill deflated by the industry price deflator. This measurement controls for the quality difference of the labor.

Value Added $p_{it}y_{it}$. Book value of the firm's value added.

Real Output y_{it}. Nominal value added deflated by an output price deflator.

Marginal Revenue Product of Capital (MRPK) R_{it}. I follow Hsieh and Klenow (2009) to construct the marginal revenue product of capital, which is $R_{it} = \alpha\phi_{it}\left(\frac{k_{it}}{l_{it}}\right)^{\alpha-1}$.

A.5 Supplementary Empirical Results

This section provides supplementary empirical results referred in the main text.

A.5.1 Productivity and leverage ratio

In this subsection, I provide the supporting evidence for the modelling of productivity as intangible assets used as collateral. I show that in the data there is a

[1]In GKKV, both tangible and intangible fixed assets are included.In our data, I do not observe the firm's intangible assets. I use the fixed assets under the tangible assets.

robust positive relation between productivity and leverage ratio, indicating that productive firms are more able to obtain debt financing.

Table A.1: Determinants of leverage ratio and R&D investment

Dependent var.:	leverage ratio	
	(1)	(2)
$\ln(\phi)$	0.562***	0.399***
	(0.092)	(0.098)
$\ln(a)$	-6.926***	-7.254***
	(0.181)	(0.145)
Controls	No	Yes
N	87329	87329
R^2	0.205	0.272

Note: control variables include firm age, ownership, province, year and 3-digit industry fixed effects. Standard errors are clustered at the city level. *** indicates significance level at 1% significance level.

A.5.2 Productivity evolution: high-tech vs. low-tech

I show the OLS estimation of the productivity process when estimating separately for high-tech and low-tech industries. I do find some heterogeneity in the endogenous productivity process. Surprisingly, I find that the productivity growth effect of R&D is larger in low-tech industry. Given that low-tech firms undertake less R&D investment, it must be that the the high costs prevent them from doing that.

A.5.3 R&D with endogenous uncertainty

A.5.3.1 Maximum-Likelihood Estimator

In particular, the log-likelihood function is given by

$$LLF = \sum_{i,t} \log \Big\{ [1 - \exp(-\psi x_{it}^{\vartheta})] g[\frac{1}{\sigma_\xi}(\ln(\phi_{it+1}) - \rho\phi_{it} - h - \mu_{jt})] \tag{A.28}$$

Table A.2: Productivity evolution for high- and low-tech industries

	dependent var.: $\ln(\phi_{t+1})$	
sectors	High-Tech	Low-Tech
$\ln(\phi_t)$	0.384^{***}	0.332^{***}
	(0.025)	(0.006)
$\ln(x_t+1)$	0.051^{***}	0.056^{***}
	(0.004)	(0.002)
industry-year FEs	Yes	Yes
$\hat{\sigma}_\xi$	1.289	1.273
N	5136	60843
R^2	0.240	0.186

Note: standard errors are heteroscedastic robust.
*** $p < 0.01$

$$+\exp(-\psi x_{it}^{\vartheta})g[\frac{1}{\sigma_\xi}(\ln(\phi_{it+1})-\rho\phi_{it}-\mu_{jt})]\Big\}$$

where $g(\cdot)$ is the density function of Standard Normal distribution. The estimates for the associated parameters are obtained by maximizing the objective log-likelihood function. Table A.3 shows the estimation results. The persistence of the productivity process is estimated to be 0.335, which is close to what I obtained using the productivity process with only exogenous productivity shocks. Also, the dispersion is similar to the estimate used in the benchmark analysis. The average improvement of productivity is 0.573. The probability of successful innovation is $\Pr(\kappa_{it}=1|x_{it}) = 1-\exp(-0.076x_{it}^{1.080})$. All of the coefficient estimates are significant at 1% significance level.

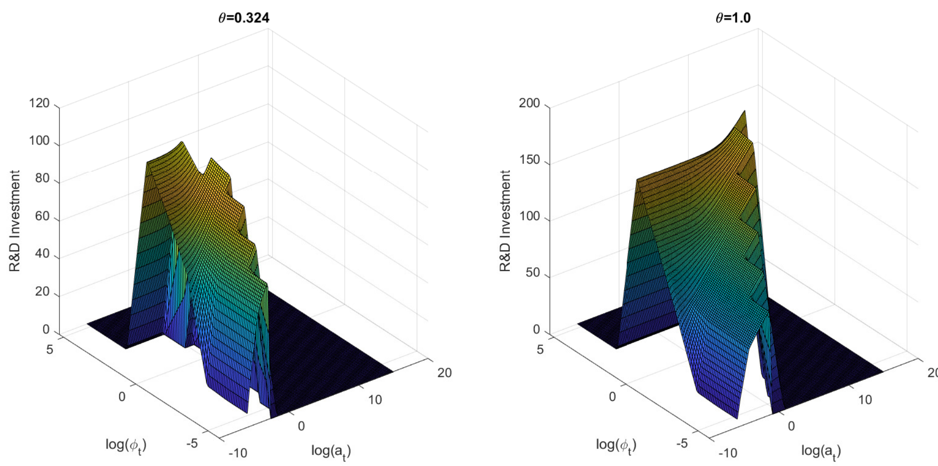
Table A.3: Productivity process with endogenous uncertain innovation outcomes

Parameters	ρ	ψ	ϑ	h	$\ln(\sigma_\xi)$
Coefficients	0.335^{***}	0.076^{***}	1.080^{***}	0.573^{***}	0.233^{***}
s.e.	(0.023)	(0.132)	(0.024)	(0.003)	(0.003)
Obs	65979				
LLF	-109129.8				

Note: estimates are obtained using Maximum Likelihood Estimator. *** $p < 0.01$

A.5.3.2 Optimal R&D policy under endogenous innovation uncertainty

Figure A.1: Optimal R&D policy: innovation process with uncertainty



The figure above shows the R&D policy functions when modelling the innovation process with uncertainty. It is clear that firms with relative lower productivity and smaller net worth choose to invest in R&D investment. This is inconsistent with the data which shows a positive partial correlation between R&D investment and net worth, as well as between R&D investment and productivity.

A.6 Computation

This section describes the main computation procedures performed in this paper.

A.6.1 Benchmark model and simulation

Our benchmark model has two continuous state variables and two continuous dynamic choice variables. Because of the fixed cost, the choice of R&D features kinks in its decision rule. Using traditional value function iteration method requires a large amount of time to accomplish the computation. Instead, I use the collocation method to solve the value function by approximating it as a combination of known basis functions. After choosing an appropriate grid for the state variables (a, ϕ), I use the alternating search algorithm to solve the bi-variate optimization problem. I find the optimization method such as Nelder-Mead algorithm and Newton's iteration method are less efficient than the alternating search method. By fixing one variable each time, the alternating search method simplifies the optimization to be a single-variable optimization. The algorithm stops whenever the new optimal values are close to the values found in the previous round. I also employ the parallel computing in Matlab to improve the computing efficiency. To avoid the problem of local optimum, I use MCMC simulations to find the minimizer of the objective GMM estimator as suggested by Chernozhukov and Hong (2003). The estimation algorithm is as follows:

1. Given a guess of (f, d) and pooled data of net worth and productivity, I solve the value function and find the optimal decisions of future net worth and R&D investment

2. Construct the objective function using the model generated data on future net worth and R&D investment for each observation

3. Obtain the Meteropolis-Hastings MCMC chains for parameters using 2000 simulations

The estimate of (f, d) is the mean of the simulated data. After I parameterize the model, I perform simulation using the solved policy functions of R&D investment and net worth to generate the path of productivity and net worth and. Then all relevant variables are computed accordingly.

A.6.2 Model Extensions

A.6.2.1 Model with R&D costs heterogeneity

I assume that f and d follows a joint log-normal distribution with correlation ρ_{fd}:

$$\begin{bmatrix} \ln f_i \\ \ln d_i \end{bmatrix} \sim \mathbf{N}\left(\begin{bmatrix} \mu_f \\ \mu_d \end{bmatrix}, \begin{bmatrix} \sigma_f^2 & \rho_{fd}\sigma_f\sigma_d \\ \rho_{fd}\sigma_f\sigma_d & \sigma_d^2 \end{bmatrix}\right)$$

I draw N realizations of f_i^0 and d_i^0 independently from the standard normal distribution $\mathbf{N}(0,1)$, putting them aside to construct the R&D costs parameters

f_i and d_i.

Step 1 Using f_i's and d_i's, I construct N realizations for each of $\ln f_i^*$ and $\ln d_i^*$ as

$$\begin{bmatrix} f_i^* \\ d_i^* \end{bmatrix} = \begin{bmatrix} \sigma_f \sqrt{1-\rho_{fd}^2} & \sigma_f \rho_{fd} \\ 0 & \sigma_d \end{bmatrix} \begin{bmatrix} f_i^0 \\ d_i^0 \end{bmatrix}$$

Step 2 For any values of μ_f and μ_d, I discretize $\ln f_i^*$ and $\ln d_i^*$ according to the characteristics of normal distribution, I obtain realizations for each of $\ln f_i$ and $\ln d_i$:

$$\ln z_i = \begin{cases} \mu_z + \sigma_z & \text{if } z_i^* \geq \mu_z + \frac{\sigma_z}{2} \\ \mu_z - \sigma_z & \text{if } z_i^* < \mu_z - \frac{\sigma_z}{2} \\ \mu_z & z_i^* \in [\mu_z - \frac{\sigma_z}{2},\, \mu_z + \frac{\sigma_z}{2}) \end{cases} \quad ;\, z \in \{f,\, d\}$$

Since I do not find a significant estimate for ρ_{fd}, ρ_{fd} is imposed to be zero in our preferred estimation. I then choose a set of values for $(\mu_f, \sigma_f, \mu_d, \sigma_d)$ to minimize the distance between the model and the data using the same moments as in the benchmark model. To avoid the local miminum, I follow Chernozhukov and Hong (2003) to obtain the Metropolis-Hastings MCMC chains using multivariate Gaussian proposal distribution.

Appendix B

Appendix to Chapter 2

B.1 Math Appendix

B.1.1 Profit maximization and revenue equation

The firm's profits maximization problem is

$$\begin{aligned} &\max_{L_{it},\, M_{it}} \{P_{it}Q_{it} - P_{Lt}L_{it} - P_{Mt}M_{it}\} \\ &s.t.\, Q_{it} = P_{it}^{-\sigma} P_t^{\sigma} Q_t \\ &\qquad Q_{it} = \Phi_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \exp\left(\beta_a a_{it}\right) \end{aligned}$$

Write the revenue as a function of the output, the first-order conditions are:

$$\left(1 - \frac{1}{\sigma}\right) \left(P_t^{\sigma} Q_t\right)^{\frac{1}{\sigma}} Q_{it}^{-\frac{1}{\sigma}} \frac{\partial Q_{it}}{\partial L_{it}} = P_{Lt} \tag{B.1}$$

$$\left(1 - \frac{1}{\sigma}\right) \left(P_t^{\sigma} Q_t\right)^{\frac{1}{\sigma}} Q_{it}^{-\frac{1}{\sigma}} \frac{\partial Q_{it}}{\partial M_{it}} = P_{Mt} \tag{B.2}$$

where $\frac{\partial Q_{it}}{\partial M_{it}} = \beta_m \frac{Q_{it}}{M_{it}}$ and $\frac{\partial Q_{it}}{\partial L_{it}} = \beta_l \frac{Q_{it}}{L_{it}}$. This implies that

$$M_{it} = \frac{P_{Lt}}{P_{Mt}} \frac{\beta_m}{\beta_l} L_{it} \tag{B.3}$$

Plugging this back to the foc for L_{it}, we obtain

$$\begin{aligned} P_{Lt} &= \beta_l \left(1-\frac{1}{\sigma}\right)\left(P_t^{\sigma} Q_t\right)^{\frac{1}{\sigma}} \frac{Q_{it}^{1-\frac{1}{\sigma}}}{L_{it}} \\ &= \beta_l \left(1-\frac{1}{\sigma}\right)\left(P_t^{\sigma} Q_t\right)^{\frac{1}{\sigma}} \left(\frac{P_{Lt}}{P_{Mt}}\frac{\beta_m}{\beta_l}\right)^{\frac{\beta_m(\sigma-1)}{\sigma}} \left(\Phi_{it} K_{it}^{\beta_k} e^{\beta_a a_{it}}\right)^{1-\frac{1}{\sigma}} L_{it}^{\frac{(\beta_l+\beta_m)(\sigma-1)}{\sigma}-1} \\ \Rightarrow\ L_{it} &= \left[\frac{P_{Lt}\left(\frac{P_{Lt}}{P_{Mt}}\frac{\beta_m}{\beta_l}\right)^{\frac{\beta_m(1-\sigma)}{\sigma}}}{\beta_l\left(1-\frac{1}{\sigma}\right)\left(P_t^{\sigma} Q_t\right)^{\frac{1}{\sigma}}}\left(\Phi_{it} K_{it}^{\beta_k}\exp\left(\beta_a a_{it}\right)\right)^{\frac{1-\sigma}{\sigma}}\right]^{\frac{\sigma}{(\beta_l+\beta_m)(\sigma-1)-\sigma}} \end{aligned} \tag{B.4}$$

Also note that the foc for L_{it} also implies that the revenue can be expressed as

$$R_{it} = \frac{\sigma P_{Lt} L_{it}}{\beta_l\left(\sigma-1\right)} \tag{B.5}$$

When $\beta_l + \beta_m = 1$, combining these two expressions and take logs yields:

$$r_{it} = \mu_0 + \mu_t + (\sigma-1)\left(\beta_k k_{it} + \beta_a a_{it} + \phi_{it}\right) \tag{B.6}$$

where

$$\mu_0 = (\sigma-1)\ln\left(\frac{\sigma-1}{\sigma}\beta_l^{\beta_l}\beta_m^{\beta_m}\right) \tag{B.7}$$

$$\mu_t = (1-\sigma)\ln\left(P_{Lt}^{\beta_l} P_{Mt}^{\beta_m}\right) + \ln\left(P_t^{\sigma} Q_t\right) \tag{B.8}$$

B.2 Supplementary Results

B.2.1 Data features

In this appendix, I present more features of the data for Chinese high-tech manufacturing firms. In particular, I will discuss the distributional characteristics for patents and the R&D-patents relation. These discussions suggest that the extensive margins of R&D and patents captures most part of the innovation activities.

Distribution of patents. Table B.1 reports the distribution of patents. We can see that the distribution of patents is highly concentrated at zero for all three types of patents. The share of firm observations with zero invention (utility) patents in the final sample is 98.01% (95.72%). This implies that only a small fraction of firms file patent applications. Focusing on the positive part of the distribution, the percentage of firm observations filing only one invention (utility) patent is 1.22% (2.22%), and that of firm observations filing two invention (utility) patents is 0.39% (0.96%). Moreover, the number of firm observations submitting no less than three invention (utility) patents account for 0.37% (1.10%) in the sample. Overall, these observations imply that the variation in the patents outcome in positive part (extensive margin) is much less significant than the change from zero to one (i.e. the extensive margin) for invention and utility patents. In other wods, among firms that have positive patent applications, most of the firms (over 50%) have only one patents. Overall, these results suggest that we have to rely on the variation in extensive margin to identify the productivity effects of the patents.

Table B.1: Distribution of patents for high-tech manufacturing firms

Patents counts	0	≥ 1	1	2	≥ 3
Invention	98.01%	1.99%	1.22%	0.39%	0.37%
Utility	95.72%	4.28%	2.22%	0.96%	1.10%

Note:the percentage represents the share of observations in the specified cohort.

R&D-patents relation. The R&D-patents linkage is an important part in the structural model to be explained in next section. Since I do not have a direct measure for innovation, I rely on the patents to measure the outcome of innovation. Different from the indicators of process and product innovation used in PRVF, I observe the number of invention patents and/or utility patents filed by each firm. To check the validity of using patents as indicators for innovation, I report the correlation between patents and R&D at both intensive and extensive margins in Table B.2. I estimate a linear model relating patents applications to R&D investment controlling for industry, and year fixed effects. I also control for firm size by use R&D intensity defined as the ratio of R&D expenditures to firm's sales.

The matrix of regression coefficients in Table B.2 show that only the correlation between the extensive margin of invention patents and R&D investment is positive and highly significant. This implies that the variation in patents outcome at the intensive margin is not well explained by the firm's R&D effort. Because R&D is the fundamental source of innovation, we will expect that the variation in patents

Table B.2: Correlation between different margins of R&D and patents

	invention patents			utility patents		
margins	extensive	intensive	both	extensive	intensive	both
extensive	.0402***	-.216	.0732***	.0444***	.165	.121***
	(.003)	(.284)	(.009)	(.003)	(.374)	(.025)
intensive	0.690***	3.214	1.631***	.403***	3.319	1.350**
	(.120)	(2.196)	(.364)	(.109)	(3.060)	(.442)
both	.883***	1.015	1.883***	.780***	2.870	2.302***
	(.110)	(2.497)	(.327)	(.107)	(3.109)	(.476)

Note: all regression contain industry and year fixed effects. Results in columns (1) and (3) are obtained using all the sample; columns (2) and (4) display the results using observations with positive patent applications. Standad errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

along the intensive margin will not have significant impact on firm's growth. Another important observation from the table is that the intensive margin of R&D is an important explanatory variable for the extensive margin of patents outcome. However, the correlation coefficient becomes much larger if we consider both margins of R&D and use R&D intensity as the indicator for R&D. This suggests that the change of R&D from zero to positive has much larger marginal impact in generating patents. In the data, the fraction of firms with zero patent is around 30%, while the fraction is increased to be 60% for firms with at least one invention or utility patent. In contrast, the mean value of R&D for firms with at least one patent is only slightly higher than firms without any patent. This confirms that the variation in R&D along the extensive margin is the main driver in explaining the patents outcome.

B.2.2 NLLS estimation

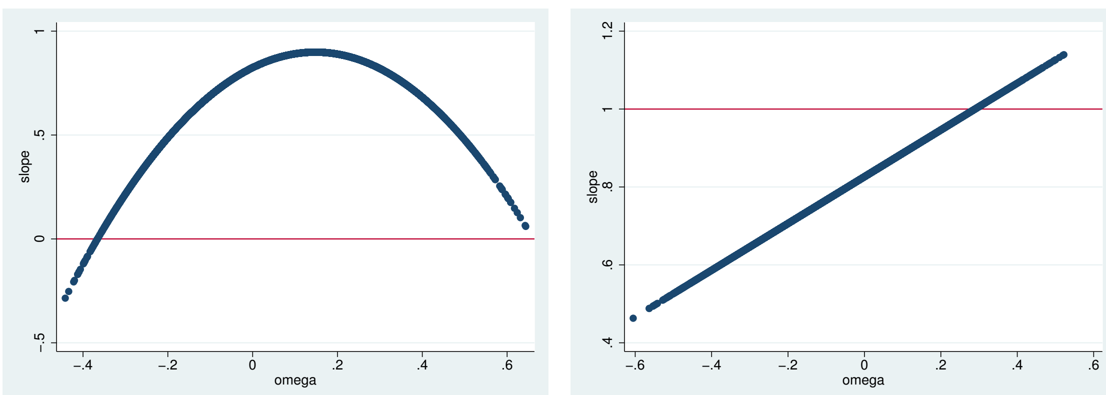
As a robustness check, we also try to parameterize $h(\cdot)$ as a quadratic function. The estimation results are reported in Table B.3. In order to use the first-stage estimates to calculate the value function, we need to check the first-order derivative of $h(\phi_{it}, d_{it}, n_{it+1}, b_{it+1})$ with respect to ϕ_{it}. To ensure that firms have incentive to invest in R&D and their value functions are bounded, we require this derivative is between 0 and 1.

Table B.3: Estimates of productivity evolution equation: supplementary results

productivity evolution equation		
ω_t	0.826**	(17.13)
ω_t^2	0.300**	(15.87)
rd_t	0.00505**	(3.35)
$rd_t \times n_{t+1}$	0.0153**	(3.04)
$rd_t \times b_{t+1}$	0.0142*	(2.85)
β_k	-0.308**	(-25.71)
N	22492	

Note:T statistics are in parentheses; * p<0.05, ** p<0.01.

Figure B.1: First-order derivative of $h(\cdot)$ with respect to ϕ_{it}



Note: in the cubic form, the number of observations that has the slope below zero is 89; in the quadratic equation,the number of observations with slope greater than one is 517.

B.2.3 Model fitness

B.2.3.1 Fitness of predicted revenues

In Figure B.2, I present a scatter plot to check the relationship between the model predicted revenue and the revenue information in the data. We can see that the predicted revenues concentrates around the 45-degree line, which indicates the revenue equation fits the data well.

Figure B.2: Model fitness for the revenue data

Note: sales are in logs of revenues in 100,000 USD.

B.2.3.2 Pooled probability of investing in R&D

Given current state, we can solve for the probability of undertaking R&D,$Pr(d = 1|\phi, d_{-1}, \mathbf{S})$ using equation (2.19). Therefore the aggregate hazad function for R&D choice can be calculated as:

$$\mathcal{H} = \frac{1}{NT}\sum_{i}^{N}\sum_{t}^{T} Pr(d_{it} = 1|\phi_{it}, d_{it-1}, \mathbf{S}_{it}) \tag{B.9}$$

On the other hand, in the data the probability of investing in R&D is given as

$$\tilde{\mathcal{H}} = \frac{1}{NT}\sum_{i}^{N}\sum_{t}^{T} d_{it} \tag{B.10}$$

I calculate the hazad function for each sector. The results are displayed in Table B.4. Overall, the estimated model predicts the probability of innovation similar to that exhibited in the data. The model-predicted pooled probability of choosing R&D is slightly higher, but the difference from the data is around 0.04. Implying that the estimated model captures the innovation decision reasonably well in terms of the probability of choosing innovation for the pooled sample.

Table B.4: Pooled probability of investing in R&D

Prob. of innovation	Pharmaceutical	Equipment	Electronics	Machinery
model	0.438	0.394	0.271	0.438
data	0.379	0.349	0.222	0.389

B.2.3.3 Transition dynamics of R&D choice

The transition probability characterizes the dynamics of transition for past R&D choice to current R&D decision. Let $rd_{-1} \in \{0,1\}$ be the R&D status in previous year and $rd \in \{0,1\}$ be the current R&D decision, then the transition probabilities are $Q(rd|rd_{-1})$. I calculate these probabilities in data using a formula as follows:

$$\tilde{Q}(rd = d'|rd_{-1} = d) = \frac{\sum_i^N \sum_t^T \mathbb{I}\{rd_{it} = d', rd_{it-1} = d\}}{\sum_i^N \sum_t^T \mathbb{I}\{rd_{it-1} = d\}} \tag{B.11}$$

where $d, d' \in \{0,1\}$. The model predicts the transition probability for each given state as:

$$Q(rd = d'|rd_{-1} = d) = \frac{1}{NT} \sum_i^N \sum_t^T Pr(rd_{it} = d'|rd_{it-1} = d, k_{it}) \tag{B.12}$$

where $Pr(rd_{it} = d'|rd_{it-1} = d, k_{it})$ can be obtained using Equation (2.19). I calculate these two transition probabilities for each sector and present it in Table B.5. First, the general patterns of the relative magnitudes of transition probabilities in the data and that predicted by the model are quite similar. In all four industries, the probability of staying in previous state is much higher than transiting to a new state. In other words, $Q(0,0)$ is larger than $Q(0,1)$, and $Q(1,1)$ is greater than $Q(1,0)$. Second, the probabilities predicted my the estimated model is very close to that observed in the data. These results suggest that the estimated model captures the transition dynamics in the R&D activities well.

Table B.5: Transition dynamics of R&D choice

sectors	source	$Q(0,0)$	$Q(0,1)$	$Q(1,0)$	$Q(1,1)$
Pharmaceutical	data	0.851	0.149	0.233	0.767
	model	0.790	0.210	0.176	0.824
Equipment	data	0.915	0.085	0.183	0.817
	model	0.875	0.125	0.128	0.872
Electronics	data	0.930	0.070	0.257	0.743
	model	0.885	0.115	0.194	0.806
Machinery	data	0.878	0.122	0.200	0.800
	model	0.828	0.172	0.150	0.850

Note: $Q(d', d) = Pr(rd = d'|rd_{-1} = d)$

B.2.4 Alternative indicator for patent quality

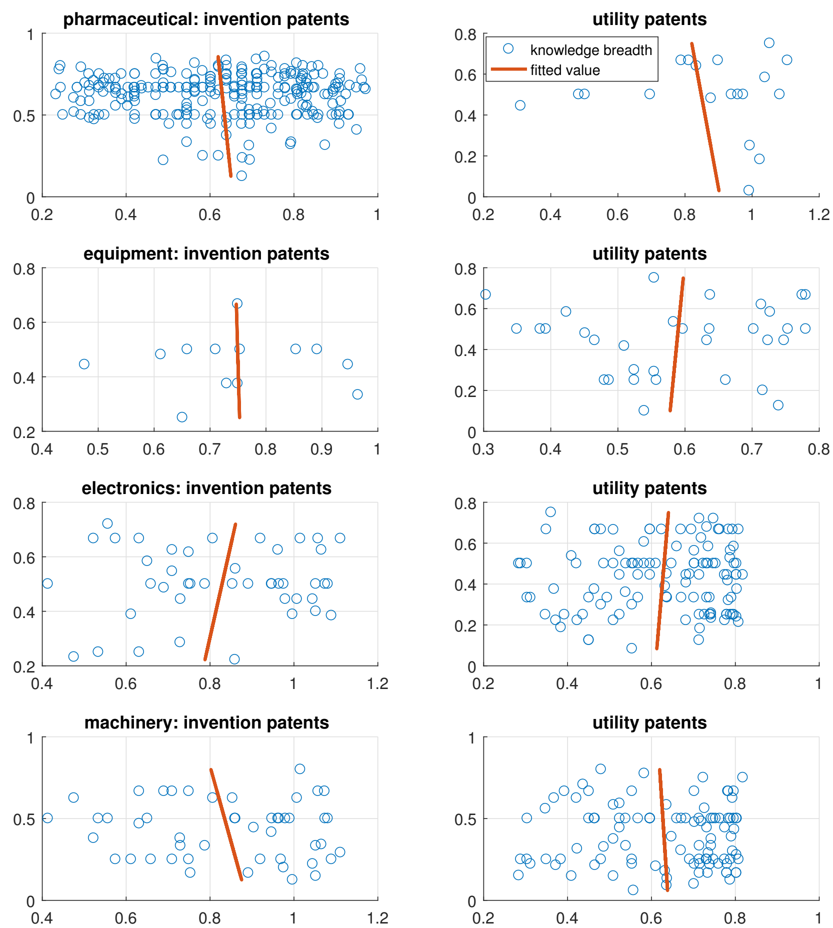
A widely used indicator for patent quality is patent citations. However, China's patent data are lack of patent citations. Dang and Motohashi (2015) propose to use the measure of knowledge breath as a proxy for the quality of patents. It is questionable whether this measure is a good indicator for the quality of patents. In Figure B.3, I display the correlation between the estimated value of patents to the indicator based on Dang and Motohashi (2015). Interestingly, we find barely no correlation between these two indicators. This may suggest that knowledge breadth measure is not a good indicator for representing the quality of the patents. At least, it does not reflect the private value of patents measured as increasing the firm's value.

B.2.5 Counterfactual analysis

B.2.5.1 Full results for all the counterfactual experiments

We conduct three experiments in which δ^m is chosen to be 10%, 15%, and 20%. The full estimation results are reported in Tables B.6, B.7, and B.8. We can observe that these results uniformly show that financing maintenance costs is more effective than financing start-up costs. More importantly, lump-sum subsidy is has larger positive impact on the firm value and the probability of innovation.

Figure B.3: Estimated patent value and knowledge breadth-based measure



Note: quality measure is based on Dang and Motohashi (2015). In all graphs, the horizontal axis is the patent quality measure based on the knowledge width of the patent claim, the vertical axis is the model-generated patent value.

Table B.6: Proportional and lump-sum subsidy: $\delta^m = .90$

policy	Proportional				Lump-sum			
sectors	pharm.	equip.	elect.	mach.	pharm.	equip.	elect.	mach.
maintenance:								
firm value ↑	0.023	0.021	0.019	0.022	0.296	0.273	0.162	0.293
per unit	0.099	0.097	0.036	0.114	1.378	1.300	0.326	1.602
inno. prob. ↑	0.010	0.008	0.006	0.010	0.038	0.028	0.019	0.036
per unit	0.078	0.082	0.033	0.092	0.334	0.292	0.113	0.380
start-up:								
firm value ↑	0.002	0.001	0.001	0.001	0.137	0.078	0.084	0.100
per unit	0.008	0.002	0.002	0.005	0.659	0.372	0.172	0.552
inno. prob. ↑	0.002	0.001	0.001	0.001	0.052	0.031	0.025	0.041
per unit	0.004	0.001	0.001	0.002	0.152	0.061	0.025	0.113

Note:units is in 10,000 US dollars.

Table B.7: Proportional and lump-sum subsidy: $\delta^m = .85$

policy	Proportional				Lump-sum			
sectors	pharm.	equip.	elect.	mach.	pharm.	equip.	elect.	mach.
maintenance:								
firm value ↑	0.035	0.033	0.029	0.034	0.454	0.416	0.248	0.447
per unit	0.102	0.100	0.037	0.117	1.436	1.342	0.340	1.661
inno. prob.↑	0.015	0.013	0.009	0.014	0.048	0.035	0.025	0.045
per unit	0.079	0.083	0.034	0.093	0.292	0.250	0.105	0.327
start-up:								
firm value ↑	0.003	0.001	0.002	0.001	0.221	0.125	0.133	0.162
per unit	0.008	0.002	0.002	0.005	0.747	0.416	0.190	0.620
inno. prob. ↑	0.002	0.001	0.001	0.001	0.076	0.046	0.037	0.060
per unit	0.004	0.001	0.001	0.002	0.168	0.068	0.028	0.126

Note:units is in 10,000 US dollars.

Table B.8: Proportional and lump-sum subsidy: $\delta^m = .80$

policy	Proportional				Lump-sum			
sectors	pharm.	equip.	elect.	mach.	pharm.	equip.	elect.	mach.
maintenance:								
firm value ↑	0.047	0.044	0.039	0.046	0.615	0.575	0.336	0.604
per unit	0.105	0.103	0.039	0.120	1.478	1.405	0.351	1.703
inno. prob. ↑	0.020	0.017	0.012	0.019	0.054	0.039	0.030	0.050
per unit	0.081	0.083	0.035	0.094	0.254	0.215	0.097	0.282
firm value ↑	0.004	0.001	0.002	0.002	0.316	0.179	0.187	0.231
per unit	0.008	0.002	0.002	0.005	0.836	0.461	0.208	0.689
inno. prob. ↑	0.003	0.001	0.001	0.002	0.099	0.060	0.049	0.078
per unit	0.004	0.001	0.001	0.002	0.182	0.075	0.030	0.138

Note:units is in 10,000 US dollars.

Appendix C

Appendix to Chapter 3

C.1 Patent Subsidy Data

Table C.1 contains information on the starting year when the patent subsidy is introduced in each province.

Table C.1: Data of patent subsidies

province	starting year	province	starting year
Beijing	2000	Henan	2002
Tianjing	2002	Hubei	2007
Hebei	2002	Hunan	2004
Shanxi	2002	Guangdong	2000
Inner Mongolia	2001	Guangxi	2004
Liaoning	2002	Hainan	2001
Jiling	2004	Chongqing	2007
Heilongjiang	2001	Sichuan	2001
Shanghai	1999	Guizhou	2006
Jiangsu	2001	Yunnan	2003
Zhejiang	2001	Xizang	2004
Anhui	2003	Shanxi	2004
Fujian	2002	Gansu	–
Jiangxi	2002	Qinghan	2006
Shangdong	2006	Ningxia	2010
		Xinjiang	2002

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Publications

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