Product Technology Adoption and Aggregate Innovation*

Qiugu He† Xuan Luo‡ Fan Zheng§

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Abstract

We document that a firm's research and development (R&D) expenditure depends on its product diversity. Combining with the fact that Chinese manufacturers often enter new product markets via technology adoption, we develop a quantitative framework of innovation and technology adoption, allowing firms to expand their product scopes. Firms adopt technologies across multiple fields to expand their knowledge base, which in turn serves as an input for subsequent innovation or adoption. Counterfactual analysis from the 2000s reveals that two-thirds of knowledge privately held by all firms is generated through adoption, accounting for one-third of aggregate innovation.

Keywords: technology adoption, innovation capability, product expansion.
JEL Codes: L16, O34, O47, O53.

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†He: Singapore Management University, qiugu.he.economics@gmail.com.

‡Luo: University of Nottingham Ningbo China, luoxuan.econ@hotmail.com.

§Zheng: Dongbei University of Finance and Economics, zhengfan@dufe.edu.cn.

1 Introduction

Endogenous growth theory has emphasized several determinants of innovation capability, including innovation experience (Klette and Kortum, 2004), productivity levels (Lucas, 2009; König et al., 2016), and competition intensity (Aghion et al., 2005). However, it overlooks the role of technology adoption in improving innovation capability through the channel of product expansion.[1] In reality, firms usually expand into new products so that different firms produce the same products, even if some are not at the frontier. These firms benefit from learning by doing in the product expansion process, which further enhances innovation capacity. In this paper, we extend the innovation workhorse model of Klette and Kortum (2004) to incorporate technology adoption, the neglected mechanism of which could have been an important driver of aggregate innovation in China.

Empirical evidence supports this mechanism. After 1978, the Chinese government systematically reduced technology adoption barriers, which facilitated firms to acquire advanced technology and expanded the manufacturing sector. This policy shift coincided with two stylized facts in China's manufacturing sector during the early 2000s. First, we find that each product market consists of many firms and there is a large proportion of multi-product firms in the economy; both witness a rising trend between year 2000 to 2006. This suggests intensifying market competition and widespread technology diffusion within each product market, as similar products often share common technological principles and cater to similar consumer demands. Second, an individual firm's R&D expenditure relies on its product diversity. Taken together, both stylized facts provide direct evidence that product diversity, mainly resulting from technology adoption, enhances innovation capability.

Tencent in China serves as a good example to further illustrate the important role of technology adoption. Founded in 1998, Tencent has become a giant with a diverse product portfolio that spans multiple industries, including internet social networking, digital gaming, media, advertising, and financial technology. Tencent's products have been widely regarded as exhibiting imitative characteristics, mirroring the functionalities of established domestic and foreign predecessors.[2] Although the newly adopted products may not be initially attractive, Tencent's deep understanding of technology and experience from successful products have made the company able to respond swiftly to market demand and continuously upgrade the products. In 2021, Tencent invested $17.7 billion in research and

[1] Firms can adopt an existing technology through specific investment and use it for production (and benefit from it in subsequent innovations) even though they are not its original inventor.

[2] Additional information regarding Tencent's technology adoption experience can be found in Appendix A.

development (R&D), an amount that was even higher than the investments made by the leading database developer, Oracle, as well as the traditional technology giant, IBM.

Motivated by the stylized facts and the Tencent example, this paper proposes a new model of innovation and technology adoption through product expansion. In the spirit of Klette and Kortum (2004), each firm attempts to engage in indirect leapfrogging innovation to monopolize multiple product markets through Bertrand competition. We extend this framework by allowing firms to enter new product markets through technology adoption. Upon successful technology adoption, firms *fully* internalize the knowledge embedded in the adopted products and compete with incumbents in the market, through Bertrand competition with capability precommitment.[3] A firm is composed of different product lines, each representing a specialized field of knowledge about its technological capability and market insights. Hence, based on their own knowledge capital stock — the number of product lines privately held, firms make innovation and adoption decisions. The aggregate knowledge capital in the economy, measured by the sum of firms' individual knowledge capital, in turn, determines the destruction rate and the rate of encountering adoption that will be applied to all firms. Our model captures rich innovation and adoption dynamics in reality, and yet remains tractable.

The model highlights a novel mechanism — the *knowledge accumulation mechanism*, related to technology adoption and learning by doing, in addition to the well-known negative profit externality for incumbents. More specifically, firms that adopt new technology would gain knowledge through production experience.[4] This learning-by-doing process fosters private knowledge capital formation for each firm, which in turn contributes to the aggregate knowledge capital build-up in the economy. Together with aggregate R&D inputs, the stock of aggregate knowledge capital — enriched by technology adoption — determines aggregate innovation. In an economy with restricted technology sharing, where innovators have perfect technology protection, each piece of knowledge capital is excludable and retained by the only innovator.[5] Upon incorporating technology adoption into this framework, firms can also accumulate knowledge capital through technology adop-

[3]In a market where innovators and adopters are unable to drive others out of market through price competition, they negotiate and form an oligopolistic structure. Similarly, in the study by Aghion et al. (2005), the laggard firm negotiates with the technology leader after the full internalization of the advanced technology.

[4]The learning-by-doing process includes experimentation, refinement and science investigation in production, and access to real market data (Arrow, 1962). Since most Chinese firms' technology base originates from adoption rather than indigenous innovation, the learning-by-doing channel is key for firms to build innovation capability.

[5]Romer (1990) considers the knowledge accumulation channel for a representative firm, yet does not account for assimilating knowledge through technology adoption. Specifically, the accumulation of knowledge A follows $\dot{A} = \delta H_A A$, where δ denotes a positive parameter and H_A denotes the rival component of technology, such as labor.

tion, which improves the marginal productivity of rival inputs (such as research labor) in the innovation production. Therefore, given the constant R&D inputs, aggregate R&D output increases with the stock of adopted knowledge.

The Chinese manufacturing sector in the 2000s is ideal for quantifying the effect of technology adoption on economic growth for several compelling reasons. First, as the largest developing country, China has heavily relied on technology adoption. Since 1978, the Chinese government has progressively built a comprehensive institutional foundation to support this process. A key strategy proposed at the national level is the pathway of "introduction, digestion, absorption, and re-innovation" to develop national science and foster technology adoption. Second, numerous Chinese firms have risen to industry leaders primarily through technology adoption. Notable examples include Huawei in telecommunications infrastructure (Mu and Lee, 2005), Lenovo in computer manufacturing (Sun et al., 2014), and many others. China's relatively low R&D intensity and short yet successful history of industrial modernization imply that technology adoption may explain the huge scale and rich product diversity of these giants, contributing to our understanding of the growth path and theoretical modeling.

By incorporating technology adoption, this model features rich market structure dynamics, wherein successful innovation yields monopolistic profits, and successful technology adoption intensifies competition and reduces innovators' profitability. Leveraging this feature and data on profitability, we employ the Simulated Method of Moments (SMM) to estimate parameters related to technology adoption and innovation efficiencies. The distribution of firm profitability is utilized to identify the underlying market structure distribution across all product markets. Meanwhile, as low R&D intensity cannot support the long tail of firm size distribution, it provides another identification for technology adoption. Besides a good fit of targeted moments, our model can fit several untargeted moments, such as the firm size distribution, and the elasticity of production expansion to the existing product scope.

In the counterfactual exercise, where the technology adoption channel is shut down, the results reveal that the average number of active producers per market decreases to one-third, the total amount of knowledge capital declines by two-thirds, and the aggregate growth rate declines by one-third. Our quantitative analysis reveals that a lower technology adoption cost drives economic growth. This growth arises because the accumulation in non-rival knowledge capital is quite cheap through technology adoption. Meanwhile, the negative impact on innovation incentives remains limited, as the adoption process also needs time to realize.

2 Literature

This paper relates to three strands of literature. First, this paper contributes to our understanding of the role of technology adoption in China's economic growth in 2000s. König et al. (2022) demonstrate that less productive firms have a high growth potential through technology adoption, which diminishes as these firms become technologically advanced. Jiang et al. (2024) demonstrate that entrants' stimulus on incumbents' innovation incentives is contingent upon the extent of technology adoption. Patent data also provide rich empirical evidence. Chinese firms assimilate knowledge in patents from multi-national firms and domestic peers, and then gradually innovate independently (Holmes et al., 2015; Ma and Zhang, 2023; Baslandze et al., 2021). Similar patterns are also well-documented in management literature; see, for example, Mu and Lee (2005) and Sun et al. (2014). Compared to the research above, our paper emphasizes the positive impacts of technology adoption on firms' innovation capability through product expansion or knowledge accumulation.

Second, this paper contributes to a growing literature on modeling aggregate innovation by heterogeneous firms. In an economy without technology adoption, incumbent firms face a destruction rate from aggregate product innovation in the economy, as in Klette and Kortum (2004), Lentz and Mortensen (2008), Luttmer (2011), Lentz and Mortensen (2016), Acemoglu et al. (2018), Jones and Kim (2018), Akcigit and Kerr (2018), Akcigit et al. (2022), Şeker et al. (2024), and Cao et al. (2024). These models assume that different firms are not allowed to produce the same products, and that each firm's private knowledge, accumulated from production, are distinct.[6] In reality, many firms produce the same products, even if some are not at the technology frontier. These firms benefit from learning by doing, which enhances their innovation capability. Our paper incorporates this channel, and the quantitative results indicate significant deviations from the Klette-Kortum world in the context of China. Our results reveal that most of the knowledge capital in Chinese firms originates from technology adoption rather than innovation.

Finally, our novel mechanism in the manufacturing sector aligns with historical evidence from the agricultural sector on how technological capability improved through learning by doing. Foster and Rosenzweig (1995) document this process in details: farmers' lack of knowledge initially acts as a barrier to technology adoption, but this barrier diminishes as they accumulate operational experience. In China, reports indicate that some farmers, after years of experience using tractors, have become providers of tractor maintenance.[7]

[6] One extension of Klette and Kortum (2004) compared to Romer (1990) is that a firm innovates based on private knowledge tying to its product lines, instead of public knowledge in society. Knowledge in different product markets is unique and distinct from one another.

[7] The source is the Dazhou Municipal Government Website in China (https://www.dazhou.gov.cn/news-

In Kenya, information barriers impede farmers' adoption of new agricultural technologies (Duflo et al., 2008). Overall, a growing understanding of technology in practice will generate a positive spillover effect on economic returns.

The remainder of this paper is organized as follows. Section 3 introduces some institutional background and motivating facts in the Chinese context. Section 4 presents the theoretical framework. Section 5 calibrates the model to the Chinese manufacturing sector in 2006 and evaluates the model performance. Section 6 quantifies the impacts on the economic state from the reduction in technology adoption cost. Finally, Section 7 concludes.

3 Institutional Background and Motivating Facts

From 1978 to 2007, China's manufacturing sector achieved remarkable progress in scale, efficiency, and complexity. During this period, the Chinese government lowered barriers to the technology adoption, and the manufacturing sector witnessed the rapid expansion despite relatively low R&D intensity.

Following the economic destruction caused by the Cultural Revolution, China's technological capability was significantly underdeveloped in 1978. In the planned economy, China's manufacturing sector was predominantly characterized by primary and light industries, featuring low productivity and limited product diversification. Despite accounting for 22.5% of the global population, China's manufacturing value added represented merely 1.7% of the world total, with an even lower global R&D share of 0.6%. This technological backwardness was evident in major industrial enterprises. For instance, Anshan Steel, the largest steel enterprise in China, produced only basic products — pig iron, crude steel, and steel sections. Similarly, the First Automobile Works (FAW) in Changchun, China's largest automobile manufacturer at that time, manufactured only a single model of Liberation (Jiefang) trucks.

By 2007, China's manufacturing sector's value-added ranking had advanced from 10th in 1978 to 2nd globally. While China's population still accounted for 20% of the global total, its manufacturing value-added share had surged to 12.1%, with global R&D expenditure share reaching 8.9%. Product diversity had also significantly improved. For instance, Shanghai Baosteel's product portfolio expanded to include around 10 varieties of steel plates (including hot-rolled, cold-rolled, and galvanized sheets), 5-6 types of steel sections (such as H-beams and I-beams), and 3-4 categories of steel tubes (including seamless

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pipes and welded pipes). Similarly, FAW Changchun also had substantially diversified its product portfolio, manufacturing various vehicle models including luxury cars, passenger cars, Jiefang heavy-duty truck series, and light commercial vehicles.

This remarkable transformation was accompanied with governments' commitment to establishing institutional frameworks and increasing national investment in science and technology. During 1978 to 1990, China's government laid the foundation for scientific and technological development through several key arrangements. These included shifting ideological focus from class struggle to modernization, restarting the college entrance examination system, establishing technology transaction markets, and positioning enterprises as the main drivers of technological advancement.

After 1990, China's government further enhanced the environment for enterprises-led technology development. The government demonstrated a sophisticated understanding of technological externalities, recognizing that breakthrough in key industries could generate spillover effects to entire industrial clusters. The policy framework encompassed several key contents. First, the government promoted industry-university-research collaboration and encouraged enterprises to develop and absorb advanced technology. By 2001, there were 5,039 university-run-enterprises, of which 40 were publicly listed companies (Eun et al., 2006). Second, priority was given to the development of telecommunications infrastructure, aimed at addressing modernization challenges and facilitating information flow across industries such as transportation, commerce, finance, and other services. According to a report by the China Internet Network Information Center in 2008, the population of internet users increased to 210 million, and 93.1% of these users agreed that the internet benefits their work and study. Third, financial support for enterprise expansion was strategically directed toward product diversification and quality improvement rather than simple capacity expansion. The investment in renovation and upgrading increased from 997 billion yuan in 1991 to 5077 billion yuan in 2000.[8] Fourth, military technologies were permitted for civilian use, and state owned enterprises (SOEs) were encouraged to establish systematic innovation mechanisms.

Along with these reforms, China's manufacturing sector expanded rapidly. Using annual statistics from mid-sized and large manufacturing firms from 1991 to 2006, the manufacturing value added grew at an average annual rate of 14.8%. However, the average R&D-to-value-added ratio remained relatively low, at just 2.1%.[9] The contrast between the

[8]Data source: the Statistical Communiqué of the People's Republic of China on the National Economic and Social Development for the Year.

[9]Data from various sources indicate that China's R&D intensity remains relatively low compared to some other major economies. For instance, in 2006, the World Bank reports that the national R&D-to-GDP ratio is 1.37% in China, 0.99% in Brazil, 2.87% in South Korea, and 2.55% in the United States.

Table 1: Status of product markets and product portfolios

	Panel A. #Firms in product markets					Panel B. Multi-product firm proportion	
Year	P25	P50	P75	Mean	SD	Balanced	Full
2000	27	71	210	196	407	31.2%	30.2%
2006	54	136	328	387	912	33.0%	31.7%

Notes: In Panel A, we choose 298 product markets continuously recorded from 2000 to 2006; refer to Appendix B.4 for details. In Panel B, we study the proportion of multi-product firms in the balanced sample from 2000 to 2006, and in the full sample. We employ the Heckman two-step estimation method to address the selection bias in the merged dataset; see Appendix B.5 for details.

rapid expansion of the manufacturing sector and low R&D intensity suggests that technology adoption played a significant role in driving the sector's rapid growth. An indicator that highlights the importance of technology adoption is the aggregate value of technology transaction contracts.[10] The total contract value for technology adoption was 1.6 times that of technology development, which is closely linked to innovation.

To conduct the analysis related to products, we merge Chinese manufacturing survey and the product quantity dataset.[11] Since the granularity of product codes is not fine enough, we refer to each code as a product category rather than an individual product. For example, code 5654 represents knitted garments, without differentiating by gender, age group, or intended usage. We document two stylized facts using the merged dataset.

Stylized Fact 1. Each product market consists of many firms, and there is a large proportion of multi-product firms in the economy; both witness a rising trend between year 2000 to 2006.

Panel A of Table 1 presents the distribution of the number of firms across 298 product markets in 2000 and 2006. The data reveal a consistent upward trend in the number of firms per product market, as reflected in increases in the 25th, 50th, and 75th percentiles, as well as the mean value. Since products within the same product market typically share similar usage, designs, and characteristics, this increased market participation not only indicates intensified competition but also suggests enhanced knowledge spillovers and technological diffusion within these markets.

Panel B of Table 1 documents the product diversification pattern from 2000 to 2006. The

[10]The data source is the Annual Statistical Report of China's National Technology Market (2003-2006). It is important to note this report does not include technology adoption expenditures incurred through the firm's own learning efforts.

[11]In section B, we introduce the two datasets, the merged results, potential problems, and our solutions.

Table 2: Product diversity and innovation investment

	log(R&D)		
	I	II	III
log(scope)	0.28***	0.20***	0.35***
	(0.003)	(0.008)	(0.009)
log(firm size)		0.52***	0.59***
		(0.002)	(0.003)
R^2	0.03	0.13	0.30

Notes: OLS. The sample includes year 2001, 2004, 2005, and 2006 when R&D expenditures were recorded. The number of observations is 296,300. In Column III, we conduct an additional robustness check by controlling for productivity, together with industry, city, ownership, and year fixed effects. Coefficient p-values are: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

merged dataset is likely to include larger firms, thereby creating a sample selection bias. To address this issue, we use the Heckman two-step estimation method to predict their product counts; see Appendix B.5 for detailed procedures. Then we focus on the balanced sample under the 'Balanced' column, and the full sample under the 'Full' column in Panel B. For the balanced sample of 76,540 unique firms, the proportion of multi-product firms increased from 31.2% to 33.0%. While the full sample also shows a modest 1.5 percentage point increase in the proportion, the number of multi-product firms grew substantially, nearly doubling from 49,333 to 94,827, driven largely by new firm establishments after 2001. These patterns suggest that Chinese firms have become increasingly capable of adopting technology or innovating to expand their product portfolios.

Stylized Fact 2. An individual firm's R&D expenditure relies on its product diversity.

We document a novel empirical pattern regarding the relationship between R&D expenditures and product diversity at the firm level. Table 2 demonstrates the positive impacts of product diversity on R&D expenditures. Column I shows that, without any controls, the estimated elasticity of R&D expenditures with respect to product scope is 0.28 and statistically significant. To address the potential concern that larger firms may invest more in R&D simply due to greater resource availability, we control for firm size in Column II. The estimated elasticity becomes 0.20 and is still statistically significant. In Column III, we conduct an additional robustness check by controlling for productivity, together with industry, city, ownership, and year fixed effects. The result remains robust. These firm-level findings support our hypothesis that product diversity enhanced firm's innovation capability.[12] To

[12] To alleviate the concerns that our results may be driven by confounding factors and reversal causality, we re-do the analysis by taking the first difference of all the variables and lagging the differenced product

address the concern that SOEs' product expansions and innovation patterns are primarily driven by government mandates, we conduct a similar analysis on the SOE subsample in Appendix B.7. The results show that SOEs also exhibit similar patterns.

4 The Model

To build a theoretical model that captures the empirical findings on firm's product expansion through innovation and technology adoption, we extend Klette and Kortum (2004) by allowing for technology adoption. In this section, we present the model setup. This section is organized as follows. First, we introduce the preferences and final good technology in Section 4.1. Second, we introduce the setup for firms in Section 4.2. This includes 1) innovation technology, and adoption technology, 2) market structure evolution, 3) the incumbent firm's value maximization problem, and 4) the entry and exit of firms. Third, we illustrate how the stationary distribution of the market structure in the balanced growth path (BGP) can be solved by considering the balance between inflow and outflow for each product market status in Section 4.3. Fourth, we provide the aggregate setting in the economy in Section 4.4. Finally, we define the general equilibrium in the BGP and discuss the key mechanisms in Section 4.5.

4.1 Preferences and Final Good Technology

The population size is fixed at L. Individuals are homogeneous and each is endowed with one unit of labor. On each date, households receive wages and dividends and consume a final good denoted as C. The discount rate across years is represented by ρ. The household's intertemporal preference over the final good C is as follows:

$$U = \int_0^\infty e^{-\rho t} logC_t dt. \tag{1}$$

The consumption good C is produced using input services from a continuum of intermediate sectors, denoted by $j \in [0, 1]$. The production function is provided in Equation (2):

diversity by one period. We find that the product diversity expansion helps predict the R&D expenditure growth; see details in empirical finding 1a in Appendix B.6.

$$logC_t = \int_0^1 log(X_{jt} z_{jt}) dj, \tag{2}$$

where X_{jt} represents the quantity of input j at date t and z_{jt} denotes the quality of input j. If the quality of product j has experienced κ instances of upgrading, the quality is defined as $z_{jt} = q^\kappa$, assuming a fixed step size of quality upgrades at q.

In our model, the version of a firm–product pair is determined not only by the technology generation but also by the technology source. Note that X_{jt} is an aggregate quantity of product j, supplied by one innovator and n technology adopters simultaneously on date t. Specifically, the quantity is given by:

$$X_{jt} = x_{jt}^{\bar{m}}(n) + n x_{jt}^{m}(n), \quad n = 0, 1, ..., n^{max};$$

$$x_{jt}^{\bar{m}}(n) = x_{jt}^{m}(n),$$

where $x_{jt}^{\bar{m}}(n)$ and $x_{jt}^{m}(n)$ denote the quantity produced by each innovator and adopter, respectively. A market consists of one innovator and n adopters. The number of adopters (n) varies from 0 to n^{max}. Here, n^{max} denotes the upper limit of the number of adopters in one market. To avoid an infinite number of adopters and heavy calculation load, we set n^{max} to be a positive integer for tractability. When $n = 0$, the innovator monopolizes the market. For simplicity, firms of the same technology equally share the market. In Section 4.2.3, we will introduce the setup for Bertrand competition with capacity precommitment, which results in an equal share of active firms in one product market.

4.2 Incumbent Firms

The economy is composed of a single type of multi-product firms, the measure of which is endogenously determined. Each firm is characterized by the statuses of the products in its product mix. This status of a product is influenced by the times of upgrading, the market structure and the knowledge source. A firm is considered active if it owns at least one product line. Conversely, a firm exists when the technology of the last product line is replaced. In addition, the economy's production knowledge is enhanced through two primary activities: innovation and technology adoption. Innovation introduces new knowledge into the economy for production. In contrast, technology adoption draws on knowledge about an existing technology that is already within the economy. This technology, while not new to the economy, is new to the technology adopter. When an innovator's technology is adopted by other firms, its profit decreases as a result of reduced market share and lower markup.

Knowledge capital serves as a crucial input in both technology adoption and innovation production functions. Meanwhile, the accumulation of knowledge capital is a result of producing new products. This concept draws inspiration from Romer (1990), who explores how a representative firm in an economy combines existing knowledge or designs within an economy to create valuable and novel products. We adopt this generation process from a micro perspective, as Klette and Kortum (2004) do, emphasizing how a firm benefits from its private knowledge base instead of public knowledge. A key distinction in our framework is that firms can also accumulate private knowledge capital through technology adoption. Through learning by doing, the internalization of adopted knowledge capital further improves a firm's innovation capability.

For both adoption and innovation production functions, the technological attributes of knowledge and labor inputs remain consistent with the literature on endogenous technology change. Labor inputs are rivalrous, so each labor input can be allocated to only one task among innovation, adoption, and production on each date. In contrast, knowledge inputs are non-rival, meaning that both innovation and adoption directly benefit from the firm's private knowledge base.

4.2.1 Technology Adoption

Intermediate producers have profit incentives to expand their product scopes through technology adoption. Both incumbents and potential entrants have such incentives. This section describes the technology adoption production function for incumbents.

Technology adoption production function. The conventional model posits that a firm's adoption rate depends on its investment, denoted by R^M units of labor. Moreover, we assume that the firm's adoption rate also depends on its private knowledge capital, k. The adoption production function can be expressed as:

$$H = G^M(R^M, k),$$

where H denotes the Poisson arrival rate of successful adoption and the function G^M is homogeneous of degree one in R^M and k. To highlight the positive learning capability from the firm knowledge base, G^M increases in k. In addition, G^M increases in R^M because a larger physical input contributes to assimilating knowledge.

Let $h \equiv \frac{H}{k}$ denote the adoption rate per unit of knowledge capital, and let $c^H(h) \equiv \frac{R^M}{k}$ represent the labor cost for a piece of knowledge capital to adopt. This cost can be specified as

$$c^H(h) = \gamma_1^H h^{\gamma_2^H},$$

where γ_1^H and γ_2^H are the two parameters governing the adoption cost function, which will be estimated.[13]

Adoption decisions directly impact the status of the product market and the firm in three significant ways: 1) The firm's adoption investment flow generates technology adoption with a Poisson arrival rate kh; 2) successful adoption adds one producer to the corresponding product market, consequently making the market more competitive; 3) successful adoption adds a new piece of knowledge capital to the firm, increasing the extensive margin of knowledge capital held by the firm to $k+1$.[14]

Since adoption does not introduce new technology into the economy, the quality of the adopted product remains the same to that of the innovated product. As a result, the aggregate extensive margin of unique knowledge capital in the economy, K^I, remains unchanged. However, the aggregate extensive margin of private knowledge capital ($K^I + K^H$) increases by one unit due to the non-rivalry of knowledge.

A firm conducts a cost-benefit analysis to make the technology adoption decision. It weighs the cost of adoption against the expected return on adoption. A firm stops investing more in adoption if the marginal cost of adoption surpasses the expected return of adoption. To capture variations in realized returns, the adopted product market is chosen randomly. Although the firm faces no uncertainty regarding the expected return, the realized return will vary depending on the realized market structure.

4.2.2 Research and Development

Firms also have incentives to accrue monopolistic profits by adding innovative products. Both incumbents and entrants have such incentives. In this section, the focus is on incumbents.

[13]This modeling approach is commonly used in the Klette-Kortum type models. It facilitates obtaining a tractable solution when solving the first-order conditions (FOCs).

[14]This assumption is motivated by the concept of the neck-and-neck status resulting from successful technological catch-up, as developed in Aghion et al. (2001, 2005), Akcigit and Ates (2023) and Jiang et al. (2024). We follow these papers in modeling each product market as an industry. Firms in the neck-and-neck status possess the same innovation capability, regardless of the underlying knowledge sources (either through innovation or technology adoption). Hence, in this setting, a firm that successfully adopts frontier technology is naturally assumed to fully absorb and internalize the underlying knowledge, thereby raising its private knowledge capital by one unit — just as the original innovator would.

Innovation technology. Consistent with convention, it is assumed that a firm's innovation rate depends on its investment in innovation (R^I unit labor) and its amount of knowledge capital (k). The innovation production function is expressed as:

$$\Lambda = G^I(R^I, k),$$

where Λ denotes its Poisson arrival rate of innovation, and the function G^I is homogeneous of degree one in R^I and k.[15]

Let $\lambda \equiv \frac{\Lambda}{k}$ denote the innovation rate per unit of knowledge capital, and let $c^I(\lambda) \equiv \frac{R^I}{k}$ denote the cost function in labor for a piece of knowledge capital. This cost can be specified as

$$c^I(\lambda) = \gamma_1^I \lambda^{\gamma_2^I},$$

where γ_1^I and γ_2^I are the two parameters governing the innovation cost function, which will be estimated.

Innovation decisions directly impact the status of the corresponding product market and the firm in four ways: 1) The firm randomly adds a product with a Poisson arrival rate $k\lambda$. 2) The successful innovator monopolizes the new product market due to quality advantage. 3) Successful innovation adds a new piece of knowledge capital to the firm, increasing the private knowledge base to $k + 1$. 4) The previous producers in this product market cease production and lose the corresponding knowledge capital because they lose the chance of learning by doing through production.

When a firm makes an innovation decision, it considers the cost of innovation (R^I units of labor) and the expected return. Since the new innovator monopolizes the product market, there is no uncertainty regarding the market structure for the innovative product.

4.2.3 Competition

For expositional simplicity, we assume that followers or potential entrants in any intermediate product market can catch up with the leader by one step. Therefore, product markets in the economy can exist in one of two states: (i) a leveled or neck-and-neck state, where the leader and multiple technology adopters compete with same technology level; or (ii) unleveled state, where the leader (successful innovator) lies one step ahead of its competitor in the same product market. This modeling approach establishes a link between competition

[15] See Appendix C.1 for an example of Cobb-Douglas production function for innovation technology.

and technology adoption.[16] This idea builds on the framework of Aghion et al. (2001) by extending it to allow for more than two firms competing in the neck-and-neck state.

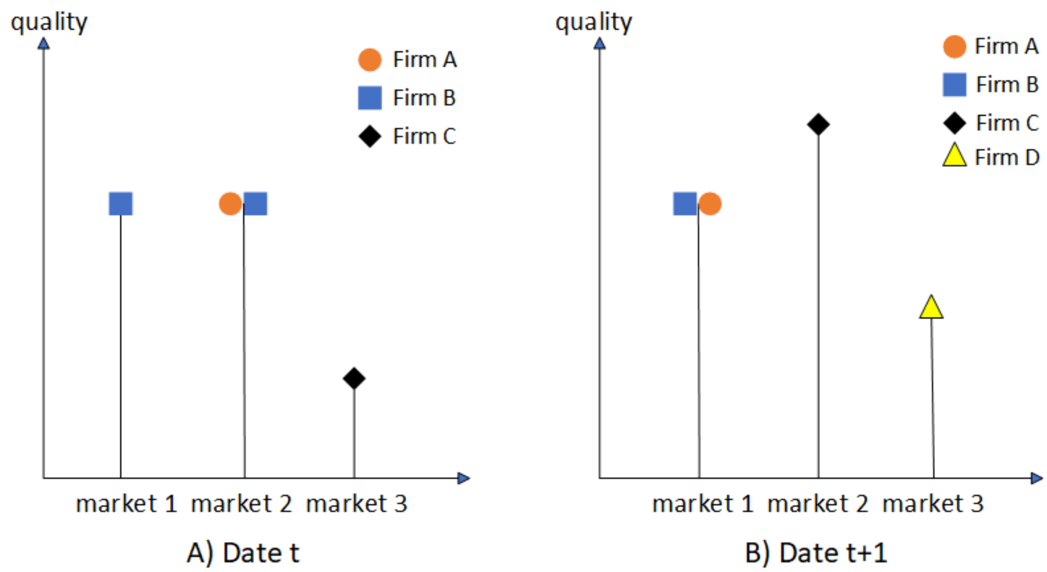
This model outlines two types of Bertrand competition that firms may encounter in an economy allowing for innovation and technology adoption. The first occurs when a new innovation arrives. The innovating firm engages in Bertrand competition to drive other active firms out of the market, thereby securing monopolistic profits. However, when a new technology is successfully adopted, Bertrand competition is not effective because the incumbent innovator lacks a marginal cost advantage to expel new adopters from the market. To ensure positive profits, firms publicly claim their production plan and then set prices to compete simultaneously. Kreps and Scheinkman (1983) formalize this oligopoly game as Bertrand competition with capacity precommitment.[17]

The market structure of each product market is shaped by the incumbents' decisions regarding innovation, adoption, as well as the presence of new entrants in the economy. In Figure 1, we demonstrate how the market structure evolves as a consequence of these decisions. The left panel exhibits three markets with different market structure: monopoly, duopoly, and again monopoly. Firm A initially produces product 2. Firm B has a broader production scope, manufacturing product 1, and 2. Firm C produces product 3. In the next date, three decisions are made and change the market structure of these markets. The right panel exhibits the new status of the economy. In market 1, Firm A adopts technology from Firm B. In market 2, Firm C innovates a new technology and drives A and B out of this market. Finally, in market 3, Firm D enters through innovation, prompting Firm C to exit. Innovations introduced in product markets 2 and 3 have improved the quality of the corresponding products at a step size q. Based on the example above, the market structure and corresponding pricing decisions can be summarized by two cases.

[16] In reality, technology adopters often produce lower-quality products compared to the previous technology leader. However, in some cases, adopters may capture a larger market share due to a profound understanding of local demands or appropriate marketing strategies. The neck-and-neck formulation is adopted here to simplify the exposition and to ensure tractability.

[17] Numerous studies, including Moreno and Ubeda (2006) and Acemoglu et al. (2009), have confirmed that this setup leads to an equilibrium that is identical to Cournot competition, even with more than two players.

Figure 1: Evolution of product markets



Notes: Panel A exhibits the technology level of products held by various firms at date t. Panel B provides an update on the situation at a subsequent point at date $t+1$. In each market, the leftmost firm is the innovator and the others are adopters.

Case 1. Monopolistic innovator. When a new innovation is introduced, the quality of the new version is q times that of the incumbent version. Let us assume that the marginal cost of the incumbent version is c. Adjusted for quality, the marginal cost of the new product is $\frac{c}{q}$. To occupy the entire market through Bertrand competition, the innovator sets its price at the follower's marginal cost, c. As a result, the innovator monopolizes the market and attains a profit rate of $1 - \frac{1}{q}$.

Case 2. Competition with n technology adopters. The unit-elasticity demand curve for one product market is given by $X = \frac{E}{p}$, based on the Cobb-Douglas production function for the final good. Here, E denotes the expenditure in the market.[18] Proposition 1 solves the problem under Bertrand competition with capacity precommitment. The proof is provided in Section C.2.

Proposition 1. *In Case 2, when the innovator and its technology adopters have identical marginal costs in a product market and conduct Bertrand competition with capacity precommitment, the markup of the product is determined by the number of adopters (n) in the market. Moreover, the markup is $\frac{1+n}{n}$. The profit is $\pi(n) = \frac{E}{1+n}\frac{1}{1+n}$. Both the markup and the profit decrease in n.*

[18] Since the measure of all product markets is set to be 1, the size of each market is equal to the aggregate market size (E).

4.2.4 Firm Problem

Before introducing the firm's problem, it is important to consider the exogenous shocks that incumbents may encounter in this model. First, each existing product faces a risk of creative destruction, represented by a Poisson hazard rate of $\mu^I(>0)$. This is known as the *destruction rate*. Second, each innovative product randomly meets adoption shocks. The Poisson hazard rate of this event, per product market, is $\mu^m(>0)$. The μ^m is called the *rate of encountering adoption*.

Consider a firm with a product portfolio represented by the vector $\boldsymbol{q}$, which serves as the state variable in the firm's problem. For each product held by the firm, there are two state variables: market structure and knowledge source. The source of knowledge is differentiated by subscripts, where I and $\bar{m}$ indicate knowledge obtained from innovation, and m denotes knowledge acquired through adoption. For example, $q^{\bar{m}}(n)$ denotes an innovative product being adopted by n firms. The firm's portfolio of innovative products suffering adoption is denoted by $\boldsymbol{q}^{\bar{m}}$. The firm's portfolio of products obtained through adoption is denoted by $\boldsymbol{q}^m$. The firm's portfolio of innovative products without adoption is denoted by $\boldsymbol{q}^I$. They satisfy $\boldsymbol{q}^{\bar{m}} \cup \boldsymbol{q}^m \cup \boldsymbol{q}^I = \boldsymbol{q}$ and $\boldsymbol{q}^{\bar{m}} \cap \boldsymbol{q}^m \cap \boldsymbol{q}^I = \emptyset$. We also use q_j to indicate the product j held by the firm. We provide an example to describe the product mix in Appendix C.3.

Given wage w and interest rate r, the firm chooses the optimal R&D effort λ, and the adoption effort h to maximize the following value function:

$$rV(\boldsymbol{q}) = \max_{\lambda,h,} \sum_{j\in\boldsymbol{q}} \begin{bmatrix} \pi(n_j) \\ -wc^I(\lambda) + \lambda\left(V\left(\boldsymbol{q} \cup_+ \{q^I\}\right) - V(\boldsymbol{q})\right) \\ -wc^H(h) + h((E_n V(\boldsymbol{q} \cup_+ \{q^m(n)\}) - V(\boldsymbol{q})) \\ +\mu^I[V(\boldsymbol{q}\backslash_- q_j) - V(\boldsymbol{q})] \\ +\mu^m[V(\boldsymbol{q}\backslash_- q_j(n_j) \cup_+ q_j(n_j+1)) - V(\boldsymbol{q})] \end{bmatrix}. \tag{3}$$

The right-hand side of Equation (3) is a summation term ($\sum$), presents the changes in value associated with decisions and shocks that affect all product lines. The summation term includes five components. The first line represents the operating profit generated by a product line with n adopters. The second and third lines capture the changes in value related to innovation and adoption decisions, respectively. The second line includes the innovation cost and the expected return from innovation. The term $V(\boldsymbol{q} \cup_+ \{q^I\})$ represents the firm's value when it introduces a new innovative product. Similarly, the third line includes the adoption cost and the benefit obtained from adoption. The term $E_n V(\boldsymbol{q} \cup_+ \{q^m(n)\})$ denotes the expected value of the firm after adding a new product line through adoption, considering the uncertainty in the market structure denoted by n. The fourth line shows the change in firm value resulting from the loss of product line j due to creative destruction rate μ^I. The term $V(\boldsymbol{q}\backslash_{\text{-}} q_j)$ represents the firm value after losing product j. Finally, the fifth line demonstrates the change in firm value caused by encountering an adoption shock. The term $V(\boldsymbol{q}\backslash_{\text{-}} q_j(n_j) \cup_{+} q_j(n_j+1))$ represents the value of the firm when the market of product j meets a new adoption. The state of the market structure for product j transitions from n_j to n_j+1. Here, n_j denotes the number of adopters in the market of product j.

Following the classical approach to solve Kelette-Kortum type models, we assume and verify that the value function can be expressed in a summation form:

$$V(\boldsymbol{q}) = \sum_{j \in \boldsymbol{q}^I} v^I + \sum_{j \in \boldsymbol{q}^{\bar{m}}} v^{\bar{m}}(n_j) + \sum_{j \in \boldsymbol{q}^m} v^m(n_j), \tag{4}$$

where v^I, $v^{\bar{m}}(n_j)$ and $v^m(n_j)$ represent product values in different states. Specifically, v^I represents the value of an innovative product that monopolizes a market. The term $v^{\bar{m}}(n_j)$ refers to the value of an innovative product that is being adopted by $n_j(>0)$ firms. Lastly, $v^m(n_j)$ represents the value of a product that is obtained through adoption, with $n_j(>0)$ adopters in its own market.

A firm's decisions and exogenous shocks shape the firm's value together. The value of each product is determined by the state, including the knowledge source and the market structure. To gain a comprehensive understanding of how these values are determined, we provide detailed information and calculations in Appendix C.4. To formalize this idea, we develop Proposition 2.

Proposition 2. *Following the summation form in Equation (4), we use the firm value function in Equation (3) to derive $2n^{max}+1$ equations to obtain the value of v^I, $\{v^{\bar{m}}(n)\}_{n=1}^{n^{max}}$, and $\{v^m(n)\}_{n=1}^{n^{max}}$, given firm decisions $\{\lambda, h\}$ and shocks $\{\mu^I, \mu^m\}$.*

Then, we use FOCs on λ, and h to solve for the firm's optimal decisions:

$$w\frac{\partial c^I(\lambda)}{\partial \lambda} = v^I, w\frac{c^H(h)}{\partial h} = Ev^m. \tag{5}$$

These expressions show that the marginal cost of each decision should equate to the change in value due to the corresponding decision.[19] Given the measure of markets with n adopters

[19]These FOCs provide a set of equations for estimating cost parameters.

$M(n)$, the expected value of an adopting product is

$$Ev^m = \sum_{n=1}^{n^{max}} \frac{M(n)}{\sum_{n=1}^{n^{max}} M(n)} v^m(n).$$

4.2.5 Entry and Exit

In the economy, there is a mass of potential entrants. Each potential entrant considers an entry flow rate $\eta > 0$, incurring an entry cost of ηF in terms of labor. Unlike in Klette and Kortum (2004), the potential entrant faces an additional decision: whether to enter through innovation or adoption. This decision depends on the associated values of the two choices: v^I for innovation and $E_n v^m(n)$ for adoption. The choice is subject to independent shocks ϵ_1 and ϵ_2, respectively.[20] The V_0 represents the value for a potential entrant. To formalize the problem faced by the potential entrants, we express it as follows:

$$rV_0 = \max_{\eta} \eta[Ev_0 - V_0] - \eta F \tag{6}$$

$$v_0 = \max\{v^I \epsilon_1, E_n v^m(n) \epsilon_2\}, \tag{7}$$

where Ev_0 denotes the expected value of a firm that owns a single product line upon successful entry. The term Ev_0 is an expectation over the two statuses:

$$Ev_0 = P_\eta^I v^I + (1 - P_\eta^I) E_n v^m(n),$$

where $P_\eta^I \equiv \frac{(v^I)^\theta}{(v^I)^\theta + (E_n v^m(n))^\theta}$.

Assuming free entry, η ensures that the net value of entry is zero. For instance, if Ev_0 is very high, resulting in a value of entry that exceeds the fixed cost, more firms will enter. This increased entry will drive down the value of v^I or $v^m(0)$ until the expected profit of entry is zero.

As each existing product line faces the same destruction rate μ^I, a firm exits the economy once it loses all of its product lines.

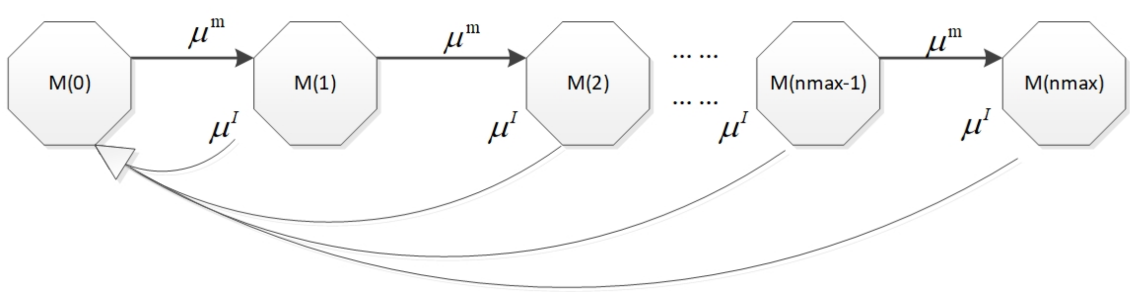
[20] Preference shock ϵ follows a type II extreme value distribution, with a cumulative distribution function given by $F(\epsilon) = exp(-\epsilon^{-\theta})$.

4.3 Evolution of Market Structure

Building upon the foundation of previous studies following Klette and Kortum (2004), which consider only a monopoly market structure, our study introduces an endogenous market structure. This complexity presents a significant challenge for solving the general equilibrium. To address this, we determine the distribution of market structure by analyzing the balanced conditions of different market structure in the BGP.

Firm decisions affect the market structure of a product market in two ways. First, successful innovation leads to a temporary monopoly. Second, successful adoption adds an additional competitor. Figure 2 illustrates the dynamics of markets of different market structures, showing the inflow and outflow for each market state. In the BGP, the following equations describe the balance between the entry and exit of each state of market structure, resulting from firm decisions and shocks. Recall that $M(n)$ is the measure of markets with n adopters, which satisfies $\sum_{n=0}^{n^{max}} M(n) = 1$.

Figure 2: Evolution of markets structure



Notes: This figure describes the inflow and outflow for markets of each market structure. The $M(n)$ denotes the measure of markets with n adopters. Each market suffers a destruction shock and adoption shock with rate μ^I and μ^m, respectively. An innovation shock results in a temporary monopoly, while an adoption shock adds one additional competitor.

For markets of state $n = 0$, inflows come from the creative destruction from all markets, $\sum_{n=0}^{n^{max}} M(n)\mu^I$. Outflows result from encountering adoption shocks, $M(0)\mu^m$, and destruction shocks, $M(0)\mu^I$. Therefore, the balance condition for market with state $n = 0$ is:

$$\sum_{n=0}^{n^{max}} M(n)\mu^I = M(0)\mu^m + M(0)\mu^I. \tag{8}$$

For markets of state $n \geq 1$ and $n < n^{max}$, inflows come from adopting technology from a market with state $n-1$. Outflows arise from encountering adoption, and destruction. The balance conditions for these states are given by:

$$M(n-1)\mu^m = M(n)(\mu^I + \mu^m), \quad 1 \leq n < n^{max}. \tag{9}$$

For markets of state $n = n^{max}$, there is no inflow or outflow from markets of state $n^{max} + 1$, and thus, the balance condition derived from Equation (9) is:

$$M(n^{max} - 1)\mu^m = M(n^{max})\mu^I. \tag{10}$$

To solve for the measure of markets as a function of shocks, we first replace $\sum_{n=0}^{n^{max}} M(n)$ with one in Equation (8). We then combine Equations (8), (9) and (10) to obtain Equation (11). Proposition 3 provides a quick calculation to numerically solve for the probability density of each market structure, M, given shocks.

Proposition 3. *In the BGP, the stationary distribution of markets of market structure,* $M \equiv [M(0) \quad M(1) \quad ... \quad M(n^{max})]'$*, is determined by the following matrix equation:*

$$\begin{pmatrix} (\mu^I + \mu^m) & 0 & 0 & 0 & 0 \\ -\mu^m & \mu^m + \mu^I & 0 & 0 & 0 \\ ... & ... & ... & ... & ... \\ ... & 0 & -\mu^m & \mu^m + \mu^I & 0 \\ 0 & 0 & 0 & -\mu^m & \mu^I \end{pmatrix} \times M = \begin{pmatrix} \mu^I \\ 0 \\ ... \\ 0 \\ 0 \end{pmatrix}. \tag{11}$$

By denoting the matrix on the left of M as A and the matrix on the right-hand side as B in Equation (11), we can quickly solve for the distribution of market states using $M = A^{-1}B$. This matrix form is highly useful for calculating the aggregate state of the economy in the model estimation and simulation.

4.4 Aggregate Setting on the Balanced Growth Path

The aggregate level of the whole economy is constrained by limited resources and requires a balance between micro-level decisions and macro-level shocks. First, the aggregate destruction rate at the macro level is a result of micro-level innovation. Second, the aggregate rate of encountering adoption is determined by the individual adoption decisions. Finally, the aggregate labor used for innovation, adoption, and production is bounded by the population size.

We introduce an aggregate amount of knowledge capital that is non-exclusively held by firms as the aggregate measure of firm–product pairs:

$$K \equiv \sum_{n=0}^{n^{max}} (n+1)M(n) = 1 + \sum_{n=0}^{n^{max}} nM(n). \tag{12}$$

Unlike the aggregate amount in Klette and Kortum (2004) models, this amount considers the non-rival attribute of knowledge, which accounts for shared knowledge across firms. Although the total amount of unique knowledge capital is fixed as $K^I = 1$, there is an additional measure of knowledge obtained through adoption. The amount of this type of knowledge, denoted by K^H, is $\sum_{n=0}^{n^{max}} nM(n)$. The increase in the amount of knowledge capital enhances the marginal productivity of rival inputs in the innovation production function.

The aggregate destruction rate is the sum of innovation efforts by incumbents, $K\lambda$, and the entry rate through innovation, ηP_η^I:

$$\mu^I = K\lambda + \eta P_\eta^I. \tag{13}$$

This equation demonstrates that the aggregate innovation depends on K, which accounts for knowledge capital obtained through innovation and adoption together. It emphasizes the importance of knowledge diffusion in aggregate innovation.

The growth rate of the economy is determined by the product of aggregate destruction rate, μ^I, and quality improvement in each innovation, $q-1$:

$$g = \mu^I(q-1). \tag{14}$$

The aggregate rate of encountering adoption is the sum of adoption effort by incumbents, Kh, and the entry rate through technology adoption, $\eta(1-P_\eta^I)$:

$$\mu^m = Kh + \eta(1-P_\eta^I). \tag{15}$$

This equation implies that the aggregate rate of encountering adoption relies on the amount of knowledge capital. Adoption improves the utilization of existing knowledge for diffusion across individual firms in the economy. It implies a multiplier effect in knowledge accumulation through adoption.

The labor market clearing condition is as follows:

$$L = \eta l^{entry} + \sum_{n=0}^{n^{max}} (n+1) M(n) \left(l^I(n) + l^H(n) + l^P(n) \right), \tag{16}$$

where l^{entry} denotes the labor used by each entrant. In addition, l^I, l^H, and l^P denote the labor used for innovation, adoption and production for each firm-product pair, respectively.[21]

The labor market clearing condition accounts for various types of labor usage. The first item on the right-hand side of Equation (16) represents the labor used for firm entry. The second item represents the aggregate labor used for innovation, technology adoption, and production.

Finally, workers spend all of their income on consumption, resulting in the consumption–output clearing condition:

$$wL = E. \tag{17}$$

4.5 General Equilibrium and the Key Mechanisms

Combining $g = r - \rho$ from the Euler equation with the utility maximization problem, we define the general equilibrium as in Section C.5. In Section C.6, we provide a method to check the uniqueness and existence of a solution in the BGP for $n^{max} = 1$, which allows one adopter to exist in each product market.

We provide a partial equilibrium analysis to explain why the knowledge accumulation via adoption might either augment or diminish innovation. The two effects underscore the two key mechanisms: the knowledge accumulation and the negative technology externality. Combing Equation (12), (13) and (14), the aggregate growth rate satisfies:

$$g \sim (K^I + K^H)\lambda, \tag{18}$$

where K^I denotes the aggregate amount of knowledge capital from innovation, fixed at one. The K^H denotes the aggregate amount of private knowledge capital obtained through adoption by all individual firms.

The two mechanisms can be outlined through Equation (18). The first effect implies a decline in the technology adoption cost can enhance the growth rate by augmenting the

[21] A firm's labor input for producing a product with status n, denoted by $l^p(n)$, can be expressed by $\frac{E/(n+1)}{\mu(n)w}$. Here, $E/(n+1)$, $\mu(n)$, and w denote sales, markup, and wage respectively.

amount of non-rival knowledge capital in the economy, K^H. The second effect indicates that a decline in the adoption cost will depress innovation incentives (λ), conditional on each piece of knowledge capital. This is due to the negative technology externality, mainly through the profit channel: As the adoption cost becomes lower, firms will expand product scope, product markets become more competitive, and the profits to be gained from each innovative product will decline accordingly. The innovation rate λ declines if the expected profit decreases. In summary, a decline in the technology adoption cost raises the extensive margin but reduces the intensive margin of innovation in the economy.

If the first effect dominates, the growth rate increases when the technology adoption cost declines. This positive effect differs from the mechanism described in Aghion et al. (2001) and Aghion et al. (2005), in which knowledge spillover intensifies market competition and firms innovate to escape competition. Conversely, if the second effect dominates, the growth rate decreases with knowledge spillover. This negative technology externality mechanism is consistent with Aghion et al. (2001) and Aghion et al. (2005). Our model introduces flexibility in the extensive margin of competing firms across product markets.

5 Estimation

Section 5.1 gives a brief introduction to empirical moments. Section 5.2 describes the identification strategy. Section 5.3 presents the indirect inference. Section 5.4 provides the main estimation results. Appendix D.1 provides detailed procedures for estimating this model.

5.1 Moments

For calibration, we use data from year 2006. There are several reasons for this choice. First, the Chinese manufacturing survey data is of relative high quality between 1998 and 2007, while the product quantity dataset is available only from 2000 to 2006. Second, the calibration relies on the assumption that the economy is on a balanced growth path. Considering potential disruptions from China's WTO accession in 2001 and the outbreak of the global financial crisis in 2007, the year 2006 provides a relatively stable window for calibration.

We prepare five types of moments using the following approach. First, we select value added to measure firm size.[22] Second, we calculate the Lerner index, or the price cost mar-

[22]A pioneer work by Lentz and Mortensen (2008) employed value added as a measure for firm size, establishing a methodological foundation that we build upon. We do not use sales to measure firm size. Sales figures can be disproportionately influenced by the cost of intermediate goods, which is not well modeled

gin, following Nickell (1996), as a measure of profitability. A firm's Lerner index is calculated as the ratio of net profit to firm scale. Net profit is established by deducting depreciation, provisions and an estimated financial cost of capital from the operating profit. Third, we count the number of product codes to measure product diversity.[23] As mentioned above, we adopt the Heckman two-step selection method to calculate product category counts for all firms.[24] Fourth, we calculate R&D intensity by dividing aggregate R&D expenditures by aggregate value added and obtain 3.3%.[25] These measures are obtained from the manufacturing survey data. Finally, we estimate the growth rate by utilizing World Bank data on China's GDP at current US prices. We obtain manufacturing value added by multiplying the GDP with the proportion of manufacturing value added of GDP. The growth rates for 2004, 2005, 2006 and 2007 are found to be 6.94%, 8.54%, 10.9% and 10.8%, respectively. To mitigate volatility due to business cycles, we compute the average value of these rates, which results in a targeted growth rate of 9.3%.

5.2 Model Identification Strategy

There are several points aiding in the identification of parameters from the data. First, the distribution of product scopes directly measures the historically accumulated product expansion through innovation and technology adoption together.

Second, the existence of a fat-tailed distribution of firm size and the low R&D intensity in China suggest that firms may heavily rely on technology adoption for expansion.[26] Meanwhile, it can be inferred that the efficiency of innovation is low relative to the efficiency of technology adoption.

without production networks. In addition, we do not use employment to measure firm size because it is not directly related to GDP.

[23]We provide evidence that product codes in the product quantity dataset are too coarse to define individual products in Appendix B.3. Therefore, we assume that each product category includes several distinct individual products. In the estimation, we find that assuming each category includes 13 individual products fits the data well.

[24]The procedure is provided in Appendix B.5.

[25]Data from China's national manufacturing annual statistics reported this indicator at 2.7%. The survey ratio is higher than the annual statistics primarily because the survey firms tend to be larger and have a higher R&D intensity. According to the Chinese manufacturing survey, the aggregate R&D-to-sale ratio is at a modest 0.4%. The considerable gap between the two measures of R&D intensity can be primarily attributed to the sector's heavy reliance on intermediate goods.

[26]The firm size distribution generated by Klette and Kortum (2004) is a logarithmic distribution, which does not support a fat tail. However, the observed distribution typically exhibits a fat tail and can be well fitted by a Pareto distribution. Our model generates a distribution that is aligned with the observations and performs better than other similar works.

Third, the distribution of firms' profit rates serves as an indicator of the level of competition, which implies the degree of technology adoption. Given the relatively weak enforcement of intellectual property rights in China, the majority of firms prefer to adopt technology to catch up with the technology leader rather than innovation. Therefore, the degree of competition is predominantly shaped by adoption. Appendix C.7 provides evidence at the industry-city level to validate this theoretical mechanism by showing that leading firms' profitability decreases in competition from technology adopters. In the dataset analyzed, approximately 75% of firms' profits are below 10%, indicating the fierce competition in the market. The modeling of competition helps identify the market structure based on the observed profit rates. Akcigit and Ates (2023) employ a similar idea for identifying knowledge spillover in the US. Instead of merely estimating an exogenous knowledge spillover parameter, we estimate the production function for adoption. Although our dataset does not record information on adoption expenditures, we utilize the equalization between the marginal cost of adoption and the expected value of adoption to infer the function. In addition, the net profit variable also partially discloses information about adoption cost parameters. Last, low R&D intensity and a fat tail of firm size distribution imply that adoption is the preferred strategy for expanding products.

Finally, the aggregate growth rate serves as an identification indicator for aggregate innovation. By considering R&D expenditures as input and the growth rate as output, we can easily obtain the efficiency of the innovation production function. Acemoglu et al. (2018) and Akcigit and Kerr (2018) use a similar strategy to identify the efficiency of the innovation production function.

5.3 Indirect Inference

There are eight parameters to be estimated: γ_1^I, γ_1^H, γ_2^I, γ_2^H, θ, q, F and ρ, as shown in Table 3. We identify these parameters using an indirect inference approach in the spirit of Lentz and Mortensen (2008) and Akcigit and Kerr (2018). This method involves generating targeted moments via simulation and then comparing these moments to those generated from the data to minimize the gap:

$$\min \sum_{i=1}^{17} \frac{(\text{model}(i) - \text{data}(i))^2}{17},$$

where each moment is indexed by i. Our indirect inference procedure targets 17 moments, which are divided into five categories. Unlike previous studies, we also include the distribution of profitability as targeted moments. This broader set of moments provides a more comprehensive understanding of the competition in the economy. As the model does not yield an analytical solution, it is impractical to directly explain how each parameter influences the moments. Based on the identification strategy discussed in Section 5.2, we provide five types of moments to capture the economy's key characteristics as follows.

Table 3: Estimated parameters

Parameters	Explanation	Value
γ_1^I	Coefficient of innovation cost function	423
γ_2^I	Power of innovation cost function	2.97
γ_1^H	Coefficient of technology adoption cost function	50
γ_2^H	Power of technology adoption cost function	3.10
θ	Power of the discrete choice function	0.002
q	Quality upgrade	1.43
F	Entry cost (1000 RMB)	2,280
ρ	Discount rate	0.040

Distribution of value added. Firm size is related to a firm's ability to expand.[27] In our model, product size tends to be small in a competitive market, and yet large in a monopolistic market. Hence, firm size does not only depend on the product scope but also on the related technology source.

Distribution of Lerner index. In our model, the profit rate in each product market, $\frac{1}{1+n}$, is determined by the market structure. The distribution of market structure is determined by μ^I, and μ^m based on Equation (11). Therefore, it reveals information about innovation and technology adoption production function, including γ_1^I, γ_2^I, γ_1^H, and γ_2^H. Moreover, the profit rate for a monopolist is $1 - \frac{1}{q}$ in our model, which aids in identifying q. Although the profit rate for each product is not directly observable, the variation in profit rates of firms is enough for identification. Moreover, the profitability provides information on estimating the adoption production function. The marginal cost of adoption firstly provides insights into the two parameters, as expressed by the equation $\gamma_1^H \gamma_2^H h^{\gamma_2^H - 1} w = Ev^m$. In the model, the value of Ev^m is mainly determined by q, μ^I, μ^m, h and λ. Same to other Klette-Kortum type models, q can be estimated from profitability and μ^I can be estimated through the growth rate. In addition, h and μ^m can be derived through profitability. Thus, we partially infer γ_1^H and γ_2^H. Combining that the net profit already excludes the innovation cost and the adoption cost, net profit $= \sum_{j \in \boldsymbol{q}} [\pi(n_j) - wc^I(\lambda) - wc^H(h)]$, we have another equation to

[27] In other works following Klette and Kortum (2004), the distribution of firm size is only influenced by the innovation rate λ, the destruction rate μ^I and entrants (η).

estimate γ_1^H and γ_2^H. Therefore, we have two equations to infer γ_1^H and γ_2^H.

Distribution of product category counts. Product category counts directly measure the accumulated product expansion through innovation or adoption. Therefore, it is directly affected by λ, h, μ^I, μ^m, and η.

Growth rate. In our model, the growth rate, denoted as g, is determined by aggregate innovation rate μ^I and the step size in quality upgrading q, as shown in the equation $g = \mu^I(q-1)$. With the known q identified from the profitability, we can directly obtain μ^I using the observed growth rate, g, in the data. Furthermore, the aggregate innovation rate μ^I, is a result of innovation by entrants and incumbents, as expressed by $\mu^I = \eta P_\eta^I + K\lambda$. The profitability, which is determined by the degree of competition, helps pin down the market structure of each product. Moreover, the aggregate number of firm–product pairs serves as a measure of knowledge capital, which is an assumption in the Klette-Kortum type model. Last, the entry cost F is pinned down by the value of new firms' products.

R&D intensity. We discipline the parameter governing the cost of innovation γ_1^I and γ_2^I through measures of the ratio of R&D expenditures to firms' value added. In our dataset, the value is directly observed. In the model, the ratio is:

$$\frac{\sum_{n=0}^{n^{max}}(n+1)M(n)\gamma_1^I\lambda^{\gamma_2^I}w}{E}.$$

Recall that E, $M(n)$, and λ are previously estimated from the firm size distribution, the profitability distribution, and the growth rate. Therefore, the relationship between the R&D intensity and the growth rate partially yields information on the two parameters γ_1^I and γ_2^I. The marginal cost of innovation provides yields additional information into the two parameters, as expressed by the equation $\gamma_1^I\gamma_2^I\lambda^{\gamma_2^I-1}w = v^I(0)$. Consequently, the two parameters can be identified through these two equations.

5.4 Estimation Results

Table 4 reports the empirical and simulated moments using the model. Overall, the model closely matches the targeted empirical moments. The corresponding parameter estimates are reported in Table 3.[28]

[28] As there is a concern that the calibration results may be specific to the single year 2006, we conduct an alternative calibration using the average moments over the period 2004–2006. This three-year window provides sufficient data to smooth out temporary fluctuations while remaining close to our benchmark year,

Our estimation yields several interesting findings. First, we find that both the innovation and technology adoption production functions exhibit decreasing return to scales (DRS) in labor input, as indicated by the estimated values of γ_2 which exceed one. Furthermore, our estimates highlight the expensive costs associated with innovation compared to technology adoption. The values of γ_1^I and γ_1^H suggest that the cost of adoption is merely one-eighth of the cost of innovation. Successful innovation improves productivity or quality by 42%. Finally, an entrepreneur invests 2.4 million RMB to establish a new firm.

5.4.1 Moment Fitting

The model closely matches the data for the value added measure. As the model in Klette and Kortum (2004) generates a logarithmic firm size distribution, which lacks a long tail, our model has achieved progress.[29]

Table 4: Data and model fit

	Data	Model		Data	Model
Value added 10%	1391	873	Lerner index 10%	-0.08	-0.09
Value added 25%	2640	2184	Lerner index 25%	0.04	0.07
Value added 50%	6090	5829	Lerner index 50%	0.17	0.20
Value added 75%	15,890	15,930	Lerner index 75%	0.32	0.27
Value added 90%	42,093	37,651	Lerner index 90%	0.48	0.33
# Product category 10%	1	1	# Product category 25%	1	1
# Product category 50%	1	1	# Product category 75%	2	2
# Product category 90%	3	3			
Growth rate	9.3%	8.9%	R&D intensity	3.3%	4.2%

Notes: The unit of value added is $1{,}000$ RMB.

The model exactly matches the data on product category counts. It is important to note that none of the previous works utilizes the information on the number of products to infer firms' capability in product expansion.

2006. We then compare the estimated parameters from the benchmark model with those from the robustness check. Overall, the estimated values from the two approaches are quite similar. For $\{\gamma_1^I, \gamma_2^H\}$, the deviation is about 5%, while for the other parameters it is less than 1%.

[29]Compared to related studies, it is worth noting that our model makes progress in fitting firm size. For example, Lentz and Mortensen (2008) provide substantial flexibility by assuming firms of three types of step size of quality upgrading, but this research only fits the mean and standard error of firm size instead of detailed percentiles. Moreover, Jones and Kim (2018), Acemoglu et al. (2018), Akcigit and Kerr (2018), and Akcigit et al. (2022) disregard the fitting of firm size.

The model demonstrates a good fit for the Lerner index distribution, capturing various market structures that firms encounter. The Lerner index at the 10th percentile is negative, which can be attributed to low profits in a competitive market despite the costs of obtaining technology. Firms may suffer losses in a highly competitive market and generate a higher profit in a market with less competition. This model expands the research scope of innovation, technology adoption or knowledge diffusion to include a flexible market structure, which is a topic often overlooked in the existing studies. Our paper addresses the issue of the limited attention given to the endogenous market structure in this field.

The model also demonstrates a close fit to the growth rate, with a rate of 8.9% compared to 9.3% observed in the data. Finally, the R&D intensity in the model is 4.2%, which is also quite close to the value of 3.3% in the data.

5.4.2 Estimated Parameters

The model parameter estimates are reported in Table 3. The model estimates two groups of production function parameters for innovation and technology adoption. Comparing the coefficients of these cost functions reveals that innovation is more expensive ($\gamma_1^I > \gamma_1^H$). This suggests that employing 423 workers leads to the acquisition of a new technology at a 100% arrival rate within one year. In contrast, only 50 workers are needed for technology adoption. Both the two cost functions exhibit DRS in labor inputs. The power of innovation (2.97) is similar to that of technology adoption (3.10).

Compared to the estimates of the Danish innovation cost function in Lentz and Mortensen (2008) ($\gamma_1^{I,Denmark} = 175, \gamma_2^{I,Denmark} = 3.7$), our results show that innovation in China is less efficient (larger γ_1^I) but exhibits a greater return to scale (smaller γ_2^I). The difference in efficiency can be attributed to factors such as lower human capital and more distortion in research in China compared to developed countries such as Denmark. The greater return to scale in China can be explained by the country's larger space and richer resources. For example, with more R&D staff involved in a research project, it is easier for Chinese firms to expand other aspects of research inputs, such as research space, land and experimentation materials in addition to labor. By comparison, Hall and Van Reenen (2000) estimate a scale parameter of 2 for US firms ($\gamma_2^{I,US} = 2$), which is slightly smaller than the parameter in our estimation. This implies that US firms are more capable of providing additional inputs to R&D than Chinese firms.

Note that data often do not record expenditures related to technology adoption. As a result, related studies have often treated technology adoption or knowledge spillover as a parameter rather than an endogenous variable. Although we do not find a direct comparison in existing studies, our estimation results are quite instructive in understanding firms' choice of knowledge source due to adoption costs. In the literature on imitation and innovation, such as Benhabib et al. (2021) and König et al. (2022), imitation is usually cheaper than innovation, which is qualitatively consistent with our estimates of adoption-related parameters. One potential comparison is Akcigit and Ates (2023), who estimate an exogenous knowledge spillover parameter rather than a technology adoption production function. They find that the knowledge spillover parameter in the US ranges between 0.03 and 0.09, which is significantly lower than the adoption arrival rate of 0.17 estimated in our model.[30] This discrepancy suggests strict IPR protection in the US and echoes the finding of Akcigit and Ates (2023) that the dominant role of a decline in the intensity of knowledge diffusion from the frontier firms to the laggard ones.

The estimated step size of quality upgrading is 1.4, which is slightly higher than the values reported in previous studies focusing on developed countries, for example 1.17 in Denmark (Lentz and Mortensen, 2008) and 1.12 or 1.13 in US (Akcigit and Kerr, 2018; Acemoglu et al., 2018). The larger innovation step size in China can be attributed to the greater amount of new knowledge obtained through innovation. Since the new knowledge in China may have been discovered in frontier countries, it is easier for China to acquire more knowledge in each innovation step. This finding aligns with the concept of catch-up in technology observed in developing countries (Acemoglu et al., 2006; Buera and Oberfield, 2020). Jiang et al. (2024), another research on China's growth and competition, estimate the step size in quality upgrading at 1.2, which is higher than the findings for developed countries. This value is lower than the estimate in our model because we use the highest profitability across firms, rather than the average profitability, to infer this parameter.

The power parameter of the discrete choice production, θ, is estimated to be 0.002. It indicates that innovation is not a perfect substitute for technology adoption when new firms choose the knowledge source of production technology to enter the market. This may be due to the government's encouragement and Chinese entrepreneurs' comparative advantage. In addition, the estimated entry cost is 2.3 million RMB.

5.4.3 Untargeted Moments

To further validate the effectiveness of our quantified model, we compare several important variables in the model with untargeted moments from the data. While the model's calibration was specifically focused on targeting only the annual state of firm size, profitability,

[30]We report the endogenous rate 0.17 in Table 6.

product diversity, R&D intensity, and the growth rate, the fitness of the model's predictions to empirical observations beyond its targeted variables would provide confidence in the model's performance.

In Table 5, we consider four types of variables to provide further validation for our model. Before the detailed analysis, we check the inequality in firm size and the distribution of the product count at a finer level. First, The firm size inequality in the model (0.74) is close to the measure in the data (0.73). The inequality index is measured by the shape parameter of the firm size distribution based on the Zipf's law. Second, compared to the median individual product count, the relative individual product counts for the 75th, 90th, and 95th percentiles are close to the relative HS6 counts in the data. In this comparison, we only consider firms above mid-size due to export selection effects.[31]

Table 5: Comparision of data and untargeted moments

	Data	Model
Firm Size Inequality	0.73	0.74
# individual product (75%) / # individual product (50%)	2.2	2.7
# individual product (90%) / # individual product (50%)	5	6.4
# individual product (95%) / # individual product (50%)	7.3	9.8
Elasticity (# New Categories, # Categories)	0.14	0.21
Elasticity (# Newly Adopted Categories, # Categories)	0.10	0.14
Corr(log(Lerner Index), # Categories)	-0.01	0.06

Notes: The firm size inequality measure (β_1) is obtained through regression $\log(\text{firm size rank}_{i,2006}) = \beta_0 - \beta_1 \log(\text{firm size}_{i,2006}) + \epsilon_{i,2006}$. For the second to fourth untargeted moments in the data, we use a HS code to represent an individual product. To estimate the elasticity of adoption in the data, the analysis is restricted to a sample of firms that invest in R&D less than 100 thousands of RMB in history. In the simulation, we generate a dynamic process that records firms' entry, exit, products addition and product removals. We choose the years 199 and 200 in the simulation to present year 2005 and 2006. We then use this panel dataset to estimate the elasticity in the model by regressions.

When comparing the model's outcomes to the data, it is essential to assess whether the model adequately captures firms' capability in product expansion. We check whether the endogenous product expansion decision in our model still relies on the existing number of product categories, as shown in the empirical finding 4a in the Appendix B.6. To do this, we analyze the data on the number of new product categories a firm added in 2006 compared to 2005. The elasticity, which measures the response of the number of new categories to the number of existing product categories, is found to be 0.14 according to the data. The model predicts a higher elasticity of 0.21. Restricted to the subsample of adopters that invest in R&D less than 100 thousands of RMB in history, we obtain the elasticity of the newly

[31] Coincidentally, the count of HS6 codes is around 13 times the count of product category codes.

adopted product category counts to the product category counts at 0.10. The counterpart in the model is estimated at 0.14. Both the data and model reveal that the elasticity of the added product scope to the existing scope is greater than the elasticity resulting from adoption. This finding supports the assumption that firms tend to innovate and adopt simultaneously.

To further check the effectiveness of our model, we examine the correlation between the logarithm of firm Lerner index and the number of product categories. The profitability reflects the degree of competition faced by the firm. The correlation is nearly zero in the data, implying that competition shocks faced by a firm are unrelated to its product diversity. The model echoes this finding: the corresponding correlation is 0.06, which is also close to zero. Although innovation improves a firm's profitability, the simultaneous adoption decision reduces the correlation between profitability and product scopes. In an economy with free entry, a firm's profitability is determined by aggregate shocks instead of the firm's status of product counts.

5.4.4 Characterization of the Economy

The endogenous variables in Table 6 provide insights into the characteristics of the economy, specifically related to innovation, technology adoption and associated shocks.

Table 6: A list of endogenous variables

Variables	Explanation	Value
Panel A. Firm decisions		
λ	Innovation arrival rate	0.07
h	Technology adoption arrival rate	0.17
Panel B. Aggregate outcomes		
μ^I	Aggregate destruction rate	0.24
μ^m	Aggregate rate of encountering adoption	0.61
K	Aggregate amount of knowledge	3.07
Panel C. Other endogenous variables		
η	Entrant flow rate	0.051
v^I	Value of a newly innovative product	3,057
$v^{\bar{m}}(1)$	Value of an innovative product with one adopter	2,350
$v^m(1)$	Value of an adopted product without other adopters	2,350
Ev^m	Expected value from a successful adoption	1,416

Notes: The unit is 1,000 RMB for v^I, $v^{\bar{m}}(1)$, $v^m(1)$ and Ev^m in Panel C.

In Panel A, the firms' decisions are reported. The innovation arrival rate is 0.07, which indicates a 0.07% probability that a newly innovated technology will arrive on the next day.[32] The technology adoption arrival rate, at 0.17, is significantly higher than the innovation arrival rate. The difference can be attributed to the low cost of technology adoption, although the value of innovation (v^I) is twice that of adoption (EV^m) in Panel C.

In Panel B, shocks are reported. The destruction rate, 0.24, implies that one-quarter of existing products will be replaced by a new generation within one year. In addition, the rate of encountering adoption is 0.61, approximately 1.5 times higher than the destruction rate. Without considering technology adoption as a source of product expansion, existing research overestimates the impacts from innovation on firm size expansion. This highlights the importance of incorporating technology adoption into standard creative destruction models, especially when the variation of firm size is used to calibrate innovation dynamics. The aggregate measure of private knowledge capital held by all firms is 3.07, given that the aggregate measure held exclusively by all firms is one. Accordingly, our model predicts that two-thirds of all private knowledge capital in the economy results from technology adoption, which emphasizes the importance of non-rivalry attribute of knowledge in the context of China.

Panel C reports the measure of entrants and values of various product states. The measure of entrants, 0.051, increases the innovation arrival rate by 0.022.[33] Compared to the aggregate rate of creative destruction, 0.24, one-twelfth of innovation is due to entrants. In addition, the value of a product depends on the market structure and the source of knowledge. The value of a newly innovated product (v^I) is largest among the four product states in this panel. When the new product is successfully adopted by one follower, only three-quarters of the value remains. When only one adopter exists in one market, the value of the original product is close to that of the adopted product. Technology adoption yields an expected value of 1,416 thousand RMB, which is approximately half that of a newly innovated product.

The model generates a favorable distribution of productivity, which steadily shifts to the right in the BGP; see Appendix D.2 for details.

[32]In the model, we assume that one year is composed of 100 days.

[33]The aggregate frequency of entrants is $\eta \times P^I_\eta = 0.051 \times 0.44 = 0.022$.

6 Impacts of Technology Adoption

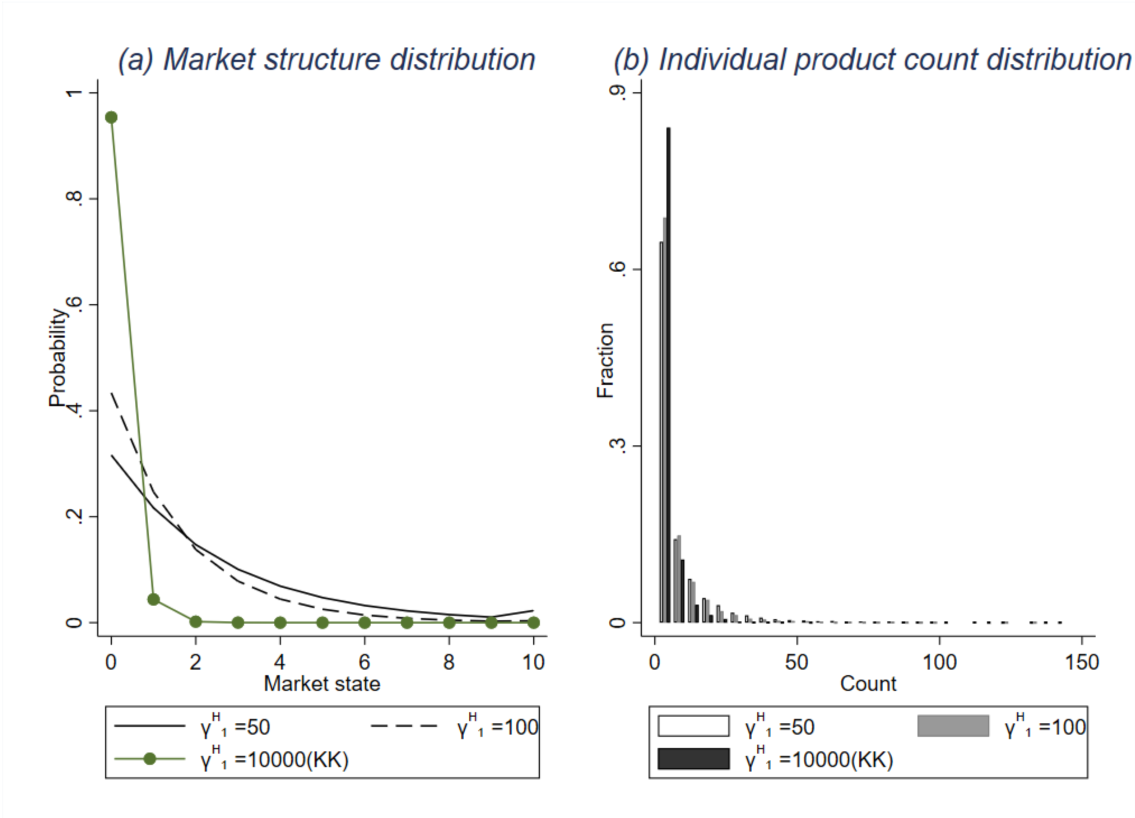
To provide further intuition on the impacts of technology adoption, we examine how economic states vary with γ_1^H, specifically when it is set to 50, 100, or $10{,}000$. The case $\gamma_1^H = 10{,}000$, simulating the prohibitively high adoption costs prior to 1978.[34] Despite the allowance for a small degree of technology adoption, this case mirrors the original setting in Klette and Kortum (2004), where technology adoption is assumed to be absent. The case $\gamma_1^H = 50$ represents the estimated adoption cost coefficient in 2006. Additionally, we provide an intermediate case of $\gamma_1^H = 100$ to illustrate the state of the economy when the adoption cost is twice as high as in 2006. We present several figures and tables to fully illustrate the impacts of the technology adoption cost reduction.

Figure 3 plots how alternative values of γ_1^H affect the distribution of market structure across product markets and the distribution of firms' individual product counts. The market structure distribution reflects not only the degree of competition but also the extent of technology diffusion across product markets in the economy. In Panel (a) of Figure 3, the dotted line indicates $\gamma_1^H = 10{,}000$ and the corresponding market structure is predominantly monopolistic. The dashed line reveals that a lower value of γ_1^H at 100 leads to a more competitive economy. The solid line, when $\gamma_1^H = 50$, exhibits the flattest distribution. This suggests that the reduction in the cost parameter γ_1^H makes firms more capable of adopting existing technology, resulting in a higher probability density of competitive markets with more adopters. The average numbers of adopters per product market are 0.04, 1.3, and 2.1 for the three cases, respectively.

Panel (b) of Figure 3 visualizes the distribution of firms' individual product counts under different values of γ_1^H. With $\gamma_1^H = 10{,}000$, 84% of firms are shown to produce fewer than six individual products. This predominance of the narrower product scope suggests that the absence of technology adoption acts as a barrier to product line expansion. As γ_1^H decreases to 100, the distribution changes markedly: only 68% of firms are now found with fewer than 6 product lines. This trend is further accentuated when γ_1^H is lowered to 50, at which point the proportion of firms with fewer than six product lines declines to 64%. These shifts illustrate a clear pattern that lower adoption costs will result in more product expansion. Consistent with the analysis above, this figure reveals that the tail for γ_1^H at 50

[34] Due to the lack of firm-level database for 1978, it is not possible to accurately estimate parameters governing the economy at that time. However, historical events during the Cultural Revolution and limited product diversity among China's largest manufacturing firms strongly suggest that adoption costs were prohibitively high. Obviously, the Cultural Revolution also had a devastating effect on innovation, but our main purpose is to isolate the effect of technology adoption cost reduction on production expansion and thus aggregate innovation in this paper. Therefore, we only experiment with alternative values of γ_1^H rather than γ_1^I.

Figure 3: Market structure and firms' individual product counts

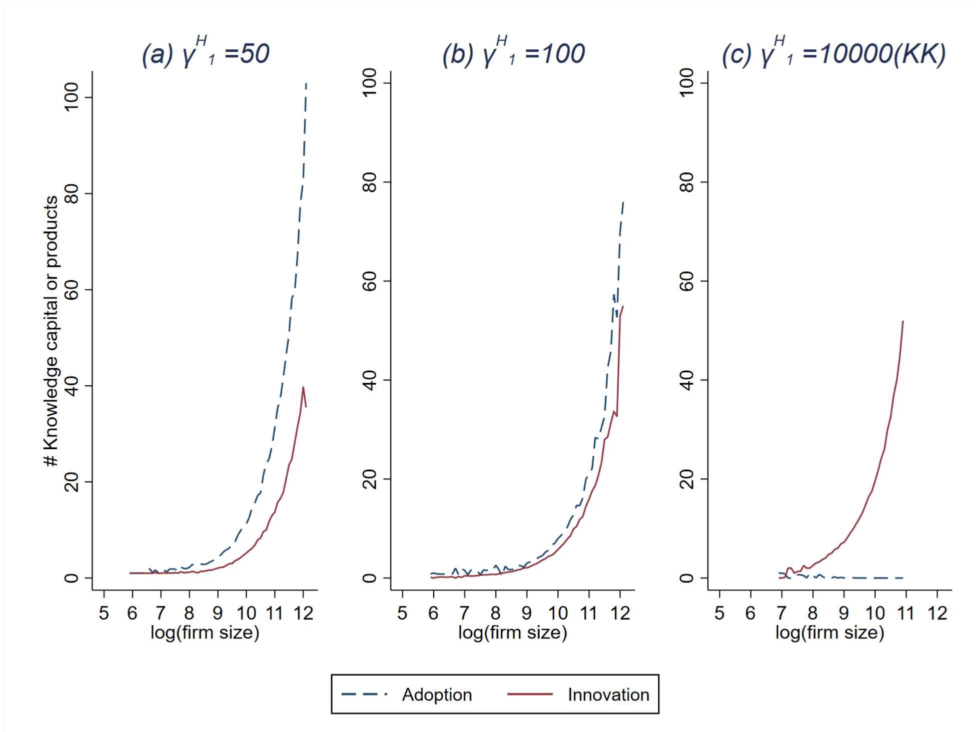


Notes: Panel (a) plots the distribution of product markets based on the number of active firms in each product market. The market state is defined by the number of technology adopters within a product market (n). Panel (b) plots the distribution of firms according to the count of product lines.

is the longest for the three cases considered.

Figure 4 shows that the reduction in technology adoption costs leads to a greater contribution of technology adoption to firm size. The number of innovative product lines increases in proportion to firm size. This suggests that larger firms have greater capacity and more resources to invest in innovation. However, new results appear when analyzing the number of adopted product lines. In the case akin to the Klette-Kortum model ($\gamma_1^H = 10{,}000$) in Panel (c), technology adoption activity is almost non-existent, as evidenced by the negligible number of adopted product lines. As the adoption cost decreases, the model predicts an increase in the number of adopted product lines, which also scales with firm size. For $\gamma_1^H = 100$, the number of adopted product lines is close to that of innovative product lines. When γ_1^H decreases to 50, the number of adopted product lines become twice that of innovative product lines.

Figure 4: Firm size and number of product lines of two sources

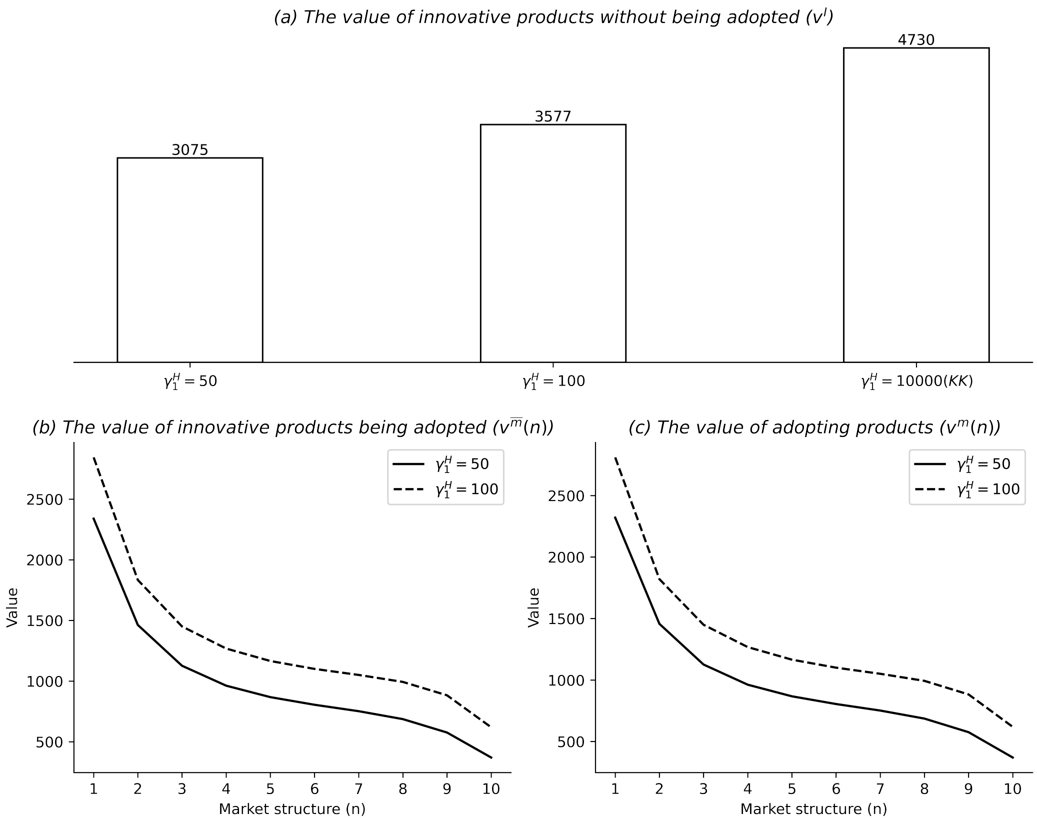


Notes: The simulated sample is divided evenly into 80 groups based on the logarithmic value of firm size. The dashed line represents the number of product lines achieved through technology adoption, while the solid line denotes the number of product lines achieved through innovation.

To show the degree of competition, Figure 5 plots the associated values of products under various market structures. It demonstrates that cheaper adoption costs tend to diminish the return or value associated with each product. In Panel (a), we compare the value of innovative products with status $n = 0$, which determines the innovation incentives directly. As γ_1^H decreases, the value declines. In Panel (b), the two lines of innovative product values decrease in market structure n. This demonstrates the negative technology externality from adoption is related to the frequency of adoption shocks confronting the innovators within an economy. In addition, Panel (b) illustrates that the dashed line, which is positioned above the solid line, indicates that an increase in γ_1^H mitigates the negative externality from adopters for innovators. In Panel (c), the shapes of the two lines of adopting product values are similar to those in Panel (b). This shows that followers' adopted products also suffer negative technology externality from other firms' adoption.

Now we explain the channels through which technology adoption affects growth. Specifically, growth is driven by (i) new entrants and (ii) existing incumbents. The aggregate innovation rate is essentially influenced by the stock of knowledge capital that has been

Figure 5: Firm–product value



accumulated through innovation (K^I) and technology adoption (K^H), as well as the rate of innovation (λ), as captured by the following equation:

$$\mu^I = \eta P_\eta^I + (K^I + K^H)\lambda. \tag{19}$$

Table 7 reports the value of each component of the aggregate innovation rate for different values of γ_1^H. We observe that as the cost parameter decreases from $\gamma_1^H = 10{,}000$ to $\gamma_1^H = 50$, there is a notable increase in the amount of knowledge capital acquired through technology adoption, with K^H rising from almost 0 to 2.07. Given that the measure of K^I is held constant at one, $K^H = 2.07$ suggests that technology adoption has become a substantial contributor to the firm's knowledge base. This channel is called the *knowledge accumulation mechanism* through technology adoption. However, the rate of innovation (λ) decreases as more technology adoption results in more negative technology externalities for existing innovation. This channel is called the *negative technology externality* from technology adoption. These two channels are not considered in other Klette-Kortum type models.

Technology adoption in our model increases the amount of private knowledge capital by two-folds but the innovation arrival rate decreases by 30%.[35] Therefore, the aggregate innovation still increases.

Table 7: Variables directly related to aggregate growth (μ^I)

	μ^I	ηP_η^I	K^I	K^H	λ
$\gamma_1^H = 50$	0.237	0.022	1	2.07	0.07
$\gamma_1^H = 100$	0.210	0.030	1	1.30	0.08
$\gamma_1^H = 10{,}000$	0.156	0.050	1	0.05	0.10

To better understand the impact of technology adoption on aggregate innovation in this model, we decompose the growth in aggregate innovation as γ_1^H decreases from $10{,}000$ to 50. The results are reported in Table 8. The model suggests that the accumulation of private knowledge significantly boosts aggregate innovation while simultaneously reducing innovation incentives for entrants and incumbents. Following the analysis in section 4.5, technology adoption contributes to 250 percentage points of aggregate innovation through the knowledge accumulation channel, while it reduces innovation of incumbents by 116 percentage points. Moreover, reduced innovation incentives of entrants lead to a decline by 34 percentage points.

Overall, the negative impacts of technology adoption on innovation incentives are outweighed by its positive contribution to innovation through knowledge accumulation. The aggregate innovation increases by around 50%.

[35] It is calculated as $1 - \frac{0.07}{0.1}$. Note that the innovation value also decreases by around 35%, a comparable magnitude. This is not a coincidence as the innovation arrival rate reflects the innovation incentives stemming from the innovation value, as clearly shown in the FOC equation for λ in equation (5). This reduction in innovation value is 35%, which is relatively small compared to the increment of private knowledge growth rate by two-folds. The modest reduction in innovation value is because innovators have a window of time to enjoy high profits before adoption occurs.

Table 8: Aggregate Innovation Growth Decomposition due to Technology Adoption Cost Reduction

	Entry	Knowledge accumulation	Incumbent incentives	Aggregate
Actual values	-0.028	0.20	-0.09	0.081
Percentage	-34%	250%	-114%	100%

Notes: We decompose the growth in aggregate innovation (μ^I) as γ_1^H decreases from 10,000 to 50, based on Equation (19). We use the value of γ_1^H in parenthesis to indicate the state of the economy. Growth in entrants innovation is obtained by $\eta(50)P_\eta^I(50) - \eta(10000)P_\eta^I(10000)$. Growth from the private knowledge channel is obtained by $[K^H(50) - K^H(10000)]\lambda(10000)$. Growth from the incumbent innovation incentive channel is obtained by $[K^I + K^H(50)][\lambda(50) - \lambda(10000)]$.

7 Conclusion

Empirical evidence from China highlights the importance of technology adoption through product expansion in driving economic growth after 1978: Both the number of producers within each product category and firms' product diversity have increased, despite historically low R&D intensity. Our firm-level evidence shows that innovation capability benefits from greater product diversity, which is primarily driven by technology adoption. These facts offer a new perspective on technological growth, particularly in developing economies like China. In reality, some firms produce the same goods as industry leaders, even though they are not at the frontier. These firms also benefit from learning by doing, through which they enhance their innovation capability. Therefore, lowering the cost of technology adoption serves as a powerful driver of innovation.

However, endogenous growth theory has not modeled this aspect yet. Standard models, such as Klette and Kortum (2004), do not leave a space for private knowledge from technology adoption. Meanwhile, the single-product frameworks in Aghion et al. (2005) and Lucas (2009) do not incorporate product expansion. To fill the gap, we propose a new model to capture this dynamic as an important driver of productivity gains, consistent with the historical experience of the Chinese manufacturing sector.

We quantify this model using data from Chinese manufacturing firms in the 2000s. The model not only fits traditional moments well, such as the firm size distribution, the growth rate, R&D intensity, but also captures the distribution of profitability and product scope. These features better reflect real-world patterns of competition and product expansion. Counterfactual exercises show that two-thirds of the technology knowledge behind product lines is obtained through technology adoption and accounts for one-third of aggregate innovation. This represents a radical departure from the Klette-Kortum framework and provides a closer match to the real world. This new framework lays a foundation to quantify a wide range of development patterns, including but not limited to knowledge transfer from foreign direct investments, imitation strategies adopted by entrants, the impact of counterfeit products, among others, particularly in emerging markets.

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Appendices

A A Case Study of Tencent in China

Tencent's products have been widely regarded as exhibiting imitative characteristics, mirroring the functionalities of established domestic and foreign predecessors. For instance, the early version of its QQ instant messaging service shares similarities with ICQ (Xie et al., 2006). Its chess and card games mirror those of Lianzhong, another Chinese gaming company. The QQ Hall and the Korean Bubble Hall also share many similarities in both game roles and game play mechanics. Even the bubble chat features of WeChat exhibits similarities to the Talk Box, a startup from Hong kong (FTimes, 2017; The Economist, 2020). Tencent's founder, Pony Ma, has openly defended the company's imitative strategy, stating, "I do not pursue innovation blindly; Microsoft and Google have also engaged in activities previously undertaken by others. The wisest approach is to study the best practices and then strive to surpass them."

The example of Tencent offers several insights about technology adoption. First, the company effectively accumulates knowledge through technology adoption across various fields, facilitating the development of new products. Failing to acknowledge these impacts may lead to underestimation of the role played by technology adoption on growth and overemphasis of the significance of strict IPR protection in fostering innovation. Second, it is worth noting that even large and productive firms such as Tencent also engage in imitation practices for fast expansion, including imitation of small firms. This observation challenges the prevailing assumptions in knowledge diffusion literature, that unproductive firms imitate more than productive firms. In reality, the peripheral products of the large and productive firms do not necessarily have advantages over the core products of smaller firms.

B Appendix to the Data

B.1 Data Sources

The primary source of data in our analysis is the Chinese manufacturing survey. This dataset was collected annually by the National Bureau of Statistics in China from 1998 to 2007. It encompasses a wide range of manufacturing firms with various ownership types. Specifically, it includes all the firms with an annual revenue surpassing 5 million RMB, as well as all the state-owned enterprises (SOEs). The manufacturing survey provides valuable information such as revenue, production cost, R&D expenditure and employment for each firm.[36] Between 2000 and 2006, the sample consists of 457,385 firms and 1.56 million firm–year observations. The average revenue is 64 million RMB.

We supplement the Chinese manufacturing survey with the production quantity dataset at the product–firm–year level between 2000 and 2006. This dataset contains a total of 729 product category codes. Since the granularity of product category codes is not fine enough, we refer to each code as a product category rather than an individual product.[37]

B.2 The Merged Dataset

By merging the two datasets, the number of firms decreases to 180,123 and the number of firm-year observations decreases to 542,785. This reduction is primarily attributable to the scope of the product quantity dataset, which is limited to products listed in the Catalog of Industrial Product Output for Above-Scale Enterprises. This catalog excludes components and semi-finished products, leading to a more focused but smaller sample. This sub-sample covers 64% of total revenue in the raw data.[38] Therefore, this merged dataset remains representative of Chinese manufacturing industries.

The manufacturing survey provides valuable information such as value added, revenue, production cost and R&D expenditure. For robustness checks, we also combine it with the quantity dataset and the customs dataset, and obtain a more detailed dataset on the number of products. These variables serve as crucial inputs for the estimation and analysis of the model parameters. The parameters of the model are identified using several key indicators, including the distribution of firm size, the distribution of number of products, the distribution of profit rates, R&D expenditure, and the growth rate.

[36] For a deep discussion of this dataset, see Brandt et al. (2012).

[37] By comparison, the World Customs Organization, which maintains the Harmonized System (HS) code system, typically has 99 2-digit headings and over 1,200 4-digit headings. Therefore, the granularity of product category codes in the production quantity dataset is finer than at the 2-digit HS level but does not reach the specificity of the 4-digit HS code level. Trade economists usually define a product at the 6-digit HS code level.

[38] Rubens (2023) also merges the Chinese manufacturing survey and the quantity dataset to research the Chinese tobacco industry. In the Chinese manufacturing survey, the sample consists of 470 tobacco firms and 2,025 observations. Combining both datasets reduces the sample size to 1,132 observations and 257 firms. This sub-sample covers 78% of total revenue in the raw data.

B.3 Product Category and HS Code

Table B.1: Three distributions of firms' product numbers in 2006

Sample Product Definition	Merged Category	Exporters Category	Exporters HS6
# Products 1%	1	1	1
# Products 5%	1	1	1
# Products 10%	1	1	1
# Products 25%	1	1	2
# Products 50%	1	1	4
# Products 75%	2	2	9
# Products 90%	3	3	20
# Products 95%	3	3	29
# Products 99%	5	6	51

In the merged dataset, only 45% of firms in 2006 produced more than one product category. However, the granularity of product variety may not be sufficient enough in the dataset, potentially leading to an understatement of the diversity of a firm's product portfolio. To address this limitation, we merge this dataset and the Chinese customs dataset that records richer data on types of products at the 8-digit Harmonized System (HS) code level. The distributions of the number of all firms' categories, exporters' categories and exporters' HS6 products are reported in Table B.1. First, the distribution of the number of product categories is close for the merged subsample and the exporter subsample, except that exporters at the 99 percentile produce one more category than the merged subsample. This implies that the selection bias in exporters is not a problem to be concerned. Regarding the number of HS6 products, more firms are multi-product firms in the customs dataset. Among the exporters in the merged dataset, the average number of product categories produced is 1.7, with an average of 8.1 unique HS6 products exported per firm. Based on the information on product categories, 45% of the exporters are classified as multi-product firms, while a larger percentage, specifically 76% of firms, export more than one HS6 product.

B.4 Procedures to Obtain the Number of Firms in Each Product Market

Product Code Unification. Between 2000 and 2006, there were two different versions of product classification codes. The first version, used from 2000 to 2003, contained 529 codes. The second version, during 2004-2006, includes 401 codes. In the transition between versions, 173 codes from the first version were discontinued after 2003, and 45 new codes were introduced in the second version.

Since the National Bureau of Statistics of China did not publish an official concordance table between the two versions, we develop a mapping methodology based on single-product firms, which are likely to maintain production of the same code across 2003 and 2004. The mapping procedure is implemented as follows:

1. Select all of the single-product firms operating in 2003.
2. Identify firm-product pairs for these firms across 2003 and 2004.
3. Categorize firms into distinct groups based on their 2003 product classification, where g^{j}_{2003} denotes the set of single-product firms producing product j.
4. For product j, we calculate the number of 2004 product classification. We use $g^{j,i}_{2004}$ to denote the set of firms that produce j in 2003 and produce i in 2004.
5. Calculate the probability as $\frac{\#g^{j,i}_{2004}}{\#g^{j}_{2003}}$, which indicates the likelihood that product i in 2004 classification is product j in 2003 classification. Establish a product mapping $j - i$ between 2003 and 2004 classifications when this probability exceeds a threshold value, which is set at 0.33 based on empirical judgement.
6. However, many-to-one and one-to-many mapping scenarios may exist. All products can map to j or i directly or indirectly are treated as a product group.

Finally, we identify 375 unique product groups. Among them, 298 product groups continuously appeared from 2000 to 2006.

Count the Number of Firms in Each Product Market. In the Chinese manufacturing survey, the number of firms in 2000 is 45% of that in 2006. In the merged dataset, this figure is 77%. To ensure consistency with the survey's firm ratio, we randomly selected 70% of firms in 2000 from the merged dataset. Then we make Panel A of Table 1 based on this subset.

B.5 Sample Selection Bias Correction

We adopt the Heckman two-step model to address the sample selection bias in product counts for the merged dataset. In the first stage, we formulate the selection equation to estimate the probability of a firm being included in the quantity production dataset. The regression is as follows:

$$\mathbb{1}\{\text{Merged Sample}\} = \alpha_0 + \alpha_1 log(age) + \alpha_2 log(capital) + \alpha_3 TFP + \text{Fixed effects} + \epsilon^{probability}.$$

Using this equation, we generate the predicted probability of being included for all observations as P_{it}.

Next, we calculate the Inverse Mills Ratio (IMR) by dividing the estimated probability density function by the cumulative distribution function.

In the second step, we use the multinomial logit model to estimate the following regression for the merged sample:

$$\#Category = \beta_0 + \beta_1 log(age) + \beta_2 log(capital) + \beta_3 TFP + \beta_4 IMR + \text{Fixed effects} + \epsilon^{count}.$$

The estimation results of the two stages are reported in Table B.2.

Table B.2: Heckman two-step model

	Step 1			Step 2		
	Dummy	# Cat.2	# Cat.3	# Cat.4	# Cat.5	# Cat.6
log(age+1)	-0.184***	0.59	-0.15***	-0.15*	-0.13	-0.29**
	(0.015)	(0.046)	(0.06)	(0.10)	(0.16)	(0.14)
log(capital+1)	0.034***	-0.03***	0.069***	0.18***	0.21***	0.30***
	(0.0013)	(0.004)	(0.007)	(0.012)	(0.02)	(0.031)
TFP	0.396***	0.056***	0.477***	1.0***	1.4***	1.70***
	(0.003)	(0.022)	(0.032)	(0.05)	(0.06)	(0.088)
IMR		-0.97***	-0.95***	-0.48***	-0.89***	-0.72*
		(0.08)	(0.12)	(0.18)	(0.27)	(0.39)
R^2	0.16			0.24		
Obs	1,399,375			531,938		

Notes: Step 1 is estimated by OLS; Step 2 by multinomial logit. Fixed effects for province, industry, year, and ownership are controlled for. Coefficient p-values are: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Finally, we predict the product category counts for the full sample. The results are reported in Table B.3. First, we compare the distribution between the data and the model prediction for the merged dataset. The prediction from the Heckman two-step model performs well. We also report the predicted distribution for the full sample, which shows a shorter right tail, as the size of firms in the full sample is averagely smaller than the merged sample.

Table B.3: Results of the Heckman two-step method

Method	Data	Prediction	Prediction
Sample	Merged	Merged	Full
# Products 1%	1	1	1
# Products 5%	1	1	1
# Products 10%	1	1	1
# Products 25%	1	1	1
# Products 50%	1	1	1
# Products 75%	2	2	1
# Products 90%	3	3	2
# Products 95%	3	3	3
# Products 99%	6	6	4
Obs	539,384	531,384	2,216,397

B.6 Additional Empirical Findings

In this subsection, we document several additional empirical findings that are consistent with the model predictions.

Empirical finding 1a. The expansion of a firm's product diversity predicts the growth of its R&D expenditure.

Recall that Stylized Fact 2 only indicates a positive correlation between an individual firm's R&D expenditure and its product diversity. Confounding factors and reversal causality may bias the results. To alleviate these concerns, we take the first difference of all the variables to remove the time-invariant firm characteristics, such as the firms' long-term strategies in product diversity and R&D, in driving the co-movements of the two key variables. We further lag the differenced product diversity by one period to further reduce endogeneity. Table B.4 reports the results. The estimated elasticity is stable between 0.11 and 0.17 across three specifications, with significance at 1% level. Hence, the expansion of a firm's product diversity predicts the growth of its R&D expenditure.

Table B.4: Product diversity expansion and R&D expenditure growth

	Δlog(R&D)		
	I	II	III
L1.Δlog(scope)	0.11***	0.14***	0.17***
	(0.028)	(0.027)	(0.029)
Δlog(firm size)		0.20***	0.018***
		(0.014)	(0.013)

Notes: OLS. The sample includes year 2005 and 2006 when R&D expenditures and their one-period lags were recorded. The number of observations is 88,232. For column III, we control for the differenced productivity, together with industry, city, ownership, and year fixed effects. Coefficient p-values are: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Empirical finding 2a. A firm's product scope is positively correlated to its R&D intensity.

Table B.5: Product diversity and R&D intensity

	log(R&D intensity)	
	I	II
log(scope)	0.18***	0.35***
	(0.008)	(0.009)
log(firm size)	-0.48***	-0.41***
	(0.002)	(0.003)
R^2	0.11	0.31

Notes: OLS. The sample includes year 2001, 2004, 2005 and 2006 when R&D expenditures are recorded. The number of observations is 296,300. R&D intensity is defined as the ratio of R&D expenditures over value added. For column III, we control for productivity, together with industry, city, ownership, and year fixed effects. Coefficient p-values are: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Empirical finding 3a. A firm's product scope is a powerful indicator for its firm size.

In Table B.6, we demonstrate a strong positive correlation between firm size and product scope. Firm size is measured using three different variables: revenue, value added and employment. The positive correlation consistently holds across all the measures. In the first row, the correlation coefficients range from 0.25 to 0.31. In the second row, the elasticity of firm size with respect to the number of product categories is estimated between 0.26 and 0.27. In the third row, the conclusion still holds even when controlling for the TFP.[39]

[39]Firms' total factor productivity (TFP) is estimated by following Ackerberg et al. (2015).

Table B.6: Firm size and product scope

	log(revenue)	log(value added)	log(employment)
Correlation	0.25	0.24	0.31
Elasticity	0.27	0.26	0.27
Elasticity (TFP controlled for)	0.28	0.29	0.26

Notes: The sample includes all firm–year observations between 2000 and 2006. Elasticity is denoted by β_1, estimated through the regression $\log(\text{size}_{it}) = \beta_0 + \beta_1 \log(\text{scope}_{it}) + \epsilon_{it}$. In the third column, we control for productivity to estimate β_1s as robustness checks. All estimated β_1s coefficients are significant at the 1% level. Ordinary least squares (OLS) regression is used.

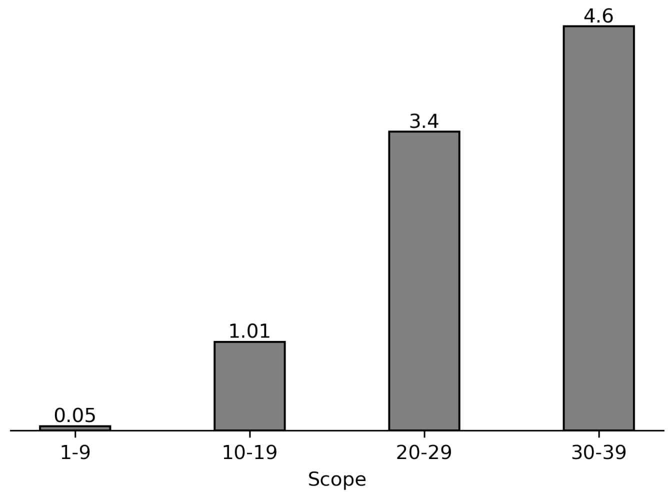
Previous empirical studies on multi-product firms have shown a similar positive relationship between firm size and product scope; see the empirical evidence from the US (Bernard et al., 2010) and India (Goldberg et al., 2010). These studies collectively suggest that differences in productivity cannot fully explain the observed gap in firm size due to product scope. Specifically, Bernard et al. (2010) find that the TFP of multi-product firms is only 2% higher than that of single-product firms, and Goldberg et al. (2010) report a difference of 1%. In our dataset, the difference in TFP between multi-product and single-product firms is 2.5%.

Empirical finding 4a. The existing product scope is a more crucial factor for the product expansion than productivity.

To examine the number of product categories added by firms, we select a sample of firms that were active in both 2000 and 2006. This yields a cross-section dataset of 66,914 firms. A new product category is defined based on the records that the product quantity was positive in 2006 but was zero in 2000. To investigate the relationship between the firm's capability to add new products and the number of existing products, we calculate the average number of new products for four distinct groups based on firms' existing product scope. The results, presented in Figure B.1, indicate that firms with 1–9, 10–19 ,20–29 and 30–39 existing product categories add on average 0.05, 1.01, 3.4, and 4.6 new product categories, respectively.[40]

[40] We exclude the group of firms with more than 40 products from this analysis, as this group comprises only five firms. The sample size is too small to be statistically reliable.

Figure B.1: Average number of new products by product scope



Notes: The sample includes firms that produced both in 2000 and 2006. By dividing the firms from year 2000 into four groups based on the number of active product categories they had, we calculate the average number of new products for each group over the period.

We demonstrate that the propensity of firms to add new product categories depends more on their existing product scope than on their productivity level. To illustrate this point, we regress the number of new product categories on product scope and productivity. Table B.7 reports the regression results. The estimated elasticity of the number of new product categories to the existing scope is 0.096 and statistically significant. Even after controlling for productivity, this estimated elasticity remains significant in column II of the table. By contrast, the elasticity with respect to the TFP is substantially smaller, at just 0.01, suggesting that existing product scope is a more crucial factor for the expansion of product categories than productivity.

Table B.7: Two determinants of product addition

	log(# new product categories)		
	I	II	III
log(scope)	0.088***	0.096***	
log(TFP)		0.014***	0.017***
R^2	0.030	0.034	0.002

Notes: OLS. The number of observations is 66,914. Coefficient p-values are: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

This relationship between firm product scope, the addition of new product categories and productivity is well-established in the literature. Bernard et al. (2010) document that

US multi-product firms are more likely to expand their product lines, with 68% adding new products compared to only 39% of single-product firms. The elasticity of new product addition in relation to productivity is notably minimal, recorded at 0.014 for single-product firms and even lower at 0.0026 for multi-product firms. A similar pattern is also documented for India (Goldberg et al., 2010) and Chile (Navarro, 2012).

B.7 Empirical Findings on SOEs

Since SOEs are responsible for executing Chinese national public affairs, there is concern that their product expansions or innovation patterns may result from administration mandates instead of product diversity or technology adoption experience. To assess whether SOEs' behavior aligns with the pattern observed in the full sample, we conduct the same analysis using only the SOE subsample. The results show that the estimated coefficients are similar, suggesting that SOEs' behavior is broadly consistent with the overall findings.

Empirical finding 1b. SOEs' product scope is positively correlated to its R&D expenditures and R&D intensity.

Table B.8: Product diversity and innovation investment (SOEs)

	log(R&D)			log(R&D intensity)		
	I	II	III	IV	V	VI
log(scope)	0.80***	0.38***	0.33***	-0.1***	0.37***	0.34***
	(0.016)	(0.016)	(0.018)	(0.016)	(0.016)	(0.018)
log(firm size)		0.49***	0.64***		-0.51***	-0.35***
		(0.005)	(0.007)		(0.005)	(0.007)
R^2	0.04	0.17	0.42	0.0006	0.14	0.40

Notes: OLS. The sample includes year 2001, 2004, 2005 and 2006 when R&D expenditures are recorded. The number of observations is 64,062. For column III, we control for productivity, together with industry, city, and year fixed effects. Coefficient p-values are: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Empirical finding 2b. The existing product scope of SOEs is a more crucial factor for the product expansion than productivity.

Table B.9: Two determinants of product addition (SOEs)

	log(# new product categories)		
	I	II	III
log(scope)	0.060***	0.061***	
log(TFP)		0.010***	0.005***
R^2	0.090	0.10	0.001

Notes: OLS. The number of observations is 13,809. Coefficient p-values are: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

C Appendix to the Model

C.1 An Example of Cobb-Douglas Production Function for Innovation Technology

Assuming $G^I(R^I, k) = Ak^\alpha(R^I)^{1-\alpha}$, $0 < \alpha < 1$, based on CRS, we derive

$$\Lambda = Ak^\alpha(R^I)^{1-\alpha} = k(A^{\frac{1}{1-\alpha}}\frac{R^I}{k})^{1-\alpha}.$$

We define $\lambda \equiv (A^{\frac{1}{1-\alpha}}\frac{R^I}{k})^{1-\alpha}$ so that $\Lambda = k\lambda$.

Given $c^I \equiv \frac{R^I}{k}$, we have

$$c^I = A^{-\frac{1}{1-\alpha}}\lambda^{\frac{1}{1-\alpha}}. \tag{C.1}$$

Since we assume that c^I is governed by the two cost parameters such that $c^I(\lambda) = \gamma_1^I\lambda^{\gamma_2^I}$, the two cost parameters can be expressed as:

$$\gamma_1^I = A^{-\frac{1}{1-\alpha}},$$

$$\gamma_2^I = \frac{1}{1-\alpha}.$$

C.2 Solution for the Static Problem

Proposition 1. *In Case 2, when the innovator and its technology adopters have identical marginal costs in a product market and conduct Bertrand competition with capacity precommitment, the markup of the product is determined by the number of adopters (n) in the market. Moreover, the markup is $\frac{1+n}{n}$. The profit is $\pi(n) = \frac{E}{1+n}\frac{1}{1+n}$. Both the markup and the profit decrease in n.*

Proof: In a product market, there are n firms with the same level of technology. The inverse demand curve, which is of unit elasticity, is $p(\{x_i\}_{i=0}^n) = \frac{E}{\sum_{i=0}^n x_i}$, where x_i denotes the quantity sold by firm i. Based on Kreps and Scheinkman (1983), the solution for the Bertrand competition with capacity precommitment can be solved via a Cournot competition game. Using Firm 0 as an example, the optimal output by Firm 0, x_0, can be derived by solving the following profit maximization problem:

$$\max_{x_0} \quad p(\{x_i\}_{i=0}^n)x_0 - cx_0. \tag{C.2}$$

By substituting the inverse demand function into Equation(C.2), we obtain:

$$\max_{x_0} \quad \frac{E}{\sum_{i=0}^n x_i}x_0 - cx_0. \tag{C.3}$$

From the FOC for x_0, we derive the optimal response function:

$$x_0 = \sqrt{\frac{E}{c}\sum_{i=1}^n x_i} - \sum_{i=1}^n x_i. \tag{C.4}$$

In equilibrium, $x_0 = ... = x_n = x$. Substituting this condition into Equation(C.4), we solve for:

$$x = \frac{E}{c}\frac{n}{(1+n)^2}$$

$$p = \frac{E}{(1+n)x} = \frac{1+n}{n}c.$$

Finally, we conclude that $p = (1+\frac{1}{n})c$ and the profit rate $\bar{\pi}(n) = \frac{1}{n+1}$. It is evident that both the markup and profit rate decrease as the number of imitators n increases. The profit is $\pi(n) = \frac{E}{1+n}\bar{\pi}(n)$. □

C.3 Product Portfolio

A product portfolio is composed of three sub-portfolios: 1) the sub-portfolio of innovative products that monopolize the corresponding markets, denoted by $\boldsymbol{q^I}$; 2) the sub-portfolio of innovative products that are suffering from adoption, denoted by $\boldsymbol{q^{\bar{m}}}$; and 3) the sub-portfolio of adopting products, denoted by $\boldsymbol{q^m}$. Taking the left panel in Figure 1 as the example, the structure for each market and the portfolio for each firm can be described in Table C.1. Panel A of the table lists the number of adopters in each market. In Panel B, we list the firms and their product portfolios.

Table C.1: Firms, markets and portfolios

Panel A. Markets and structure		
Market	Number of adopters	Structure
1	0	Monopoly
2	1	Duopoly
3	0	Monopoly
Panel B. Firm-specific product portfolios		
Firm	Portfolio	
A	$\boldsymbol{q^{\bar{m}}}=\{2\}$	
B	$\boldsymbol{q^I}=\{1\}$, $\boldsymbol{q^m}=\{2\}$	
C	$\boldsymbol{q^I}=\{3\}$	

C.4 Solving the Value Function

Proposition 2 *Following the summation form in Equation (4), we use the firm value function in Equation (3) to derive $2n^{max}+1$ equations to obtain the value of v^I, $\{v^{\bar{m}}(n)\}_{n=1}^{n^{max}}$, and $\{v^m(n)\}_{n=1}^{n^{max}}$, given firm decisions $\{\lambda, h\}$ and shocks $\{\mu^I, \mu^m\}$.*

Proof: First, we guess and verify that the summation in Equation (4) solves the value function in Equation (3). The details of the $2n^{max}+1$ product values are guessed by Equations (C.5), (C.6) and (C.7). Substituting the three equations into Equation(4) , we obtain Equation(3) and verify the summation form.

$$v^I = \frac{\pi(0) + (-wC^I(\lambda) + \lambda v^I(0)) + (-wC^H(h) + hEv^m) + \mu^m v^{\bar{m}}(1)}{r - \lambda + \mu^I + \mu^m} \tag{C.5}$$

$$v^{\bar{m}}(n) = \frac{\pi(n) + (-wC^I(\lambda) + \lambda v^I(0)) + (-wC^H(h) + hEv^m) + \mu^m v^{\bar{m}}(n+1)}{r + \mu^I + \mu^m} \tag{C.6}$$

$$v^m(n) = \frac{\pi(n) + (-wC^I(\lambda) + \lambda v^I(0)) + (-wC^H(h) + hEv^m) + \mu^m v^m(n+1)}{r + \mu^I + \mu^m}. \tag{C.7}$$

Second, we show that $v^I, \{v^{\bar{m}}(n)\}_{n=1}^{n^{max}}, \{v^m(n)\}_{n=1}^{n^{max}}$ can be solved through the $2n^{max} + 1$ equations given by Equations (C.5), (C.6) and (C.7) if h, λ, μ^I, and μ^m are known.

We can substitute Equations (C.5), (C.6) and (C.7) into the value function and verify it.
□

C.5 General Equilibrium

The general equilibrium is the allocation of resources to production, innovation, adoption, and entry $\{l^P(n), l^I(n), l^H(n), l^{entry}\}$, the likelihood of entrants and incumbent firms' choice of innovation P_η^I, the innovation rate λ, the adoption rate h, the price markup in markets without adoption μ^{lead}, the markup in markets with $n(> 0)$ adopters $\{\mu^{neck}(n)\}$, the aggregate destruction rate μ^I, the rate of encountering adoption μ^m, and the distribution of the product market structure $\{M(n)\}$, the wage rate w and the real interest rate r:

(i) Given the wage rate w, workers maximize utility through utility functions (Equations 1 and 2) and obtain $g = r - \rho$ from the Euler equation.

(ii) The entrant firm solves the entry problem (Equation 6).

(iii) The leading firm sets the markup $\mu^{lead} = \frac{q}{q-1}$ to drive existing producers out of the market if the product is newly innovated.

(iv) When n adopters are in a neck-and-neck state, meaning that they have the same advanced technology as the innovator, they compete with each other using a markup $\mu^{neck}(n) = \frac{n+1}{n}$ in a Bertrand competition with capacity precommitment.

(v) Firms maximize the value of their portfolio (Equation 3) by choosing the innovation rate λ, adoption rate h.

(vi) The aggregate creative destruction shock μ^I results from individual firm innovation (Equation 13).

(vii) The rate of encountering adoption μ^m is determined by the firm's adoption decisions (Equation 15).

(viii) The labor market clearing condition is satisfied (Equation 16).

(ix) The wage rate w is determined such that it balances the aggregate income of workers and consumption (Equation 17).

(x) The distribution of the market structure on the BGP satisfies Equation (11).

C.6 Uniqueness and Existence of the Equilibrium

In this section, we show that there is a unique solution (μ^I, μ^m) for any given $(\eta, \lambda, h, P^I_\eta)$ in BGP. We only consider a simplified version where $n^{max} = 1$. For the more complex cases ($n^{max} > 1$), the way to verify the uniqueness and existence of the solution is similar but requires a heavier calculation load. The BGP satisfies:

$$\begin{pmatrix} \mu^I + \mu^m & 0 \\ -\mu^m & \mu^I \end{pmatrix} \times M = \begin{pmatrix} \mu^I \\ 0 \end{pmatrix} \tag{C.8}$$

$$\mu^I = \eta P^I_\eta + \lambda \begin{pmatrix} 1 & 2 \end{pmatrix} M \tag{C.9}$$

$$\mu^m = \eta P^H_\eta + h \begin{pmatrix} 1 & 2 \end{pmatrix} M. \tag{C.10}$$

Equation (C.8) can be written as $AM = B$. First, we use the elements of matrix A to obtain the reverse of A directly:

$$A^{-1} = \frac{1}{(\mu^I + \mu^m)(\mu^I)} \begin{pmatrix} \mu^I & \mu^m \\ 0 & \mu^I + \mu^m \end{pmatrix}. \tag{C.11}$$

To obtain M, we substitute Equation (C.11) into Equation (C.8) to replace A^{-1} and obtain:

$$M = A^{-1} \begin{pmatrix} \mu^I \\ 0 \end{pmatrix} = \frac{1}{(\mu^I + \mu^m)(\mu^I)} \begin{pmatrix} (\mu^I)^2 \\ 0 \end{pmatrix}. \tag{C.12}$$

Substituting Equation (C.12) into the second and third equations, we get:

$$\mu^I = \eta P^I_\eta + \lambda \frac{(\mu^I)^2}{(\mu^I + \mu^m)(\mu^I)}$$

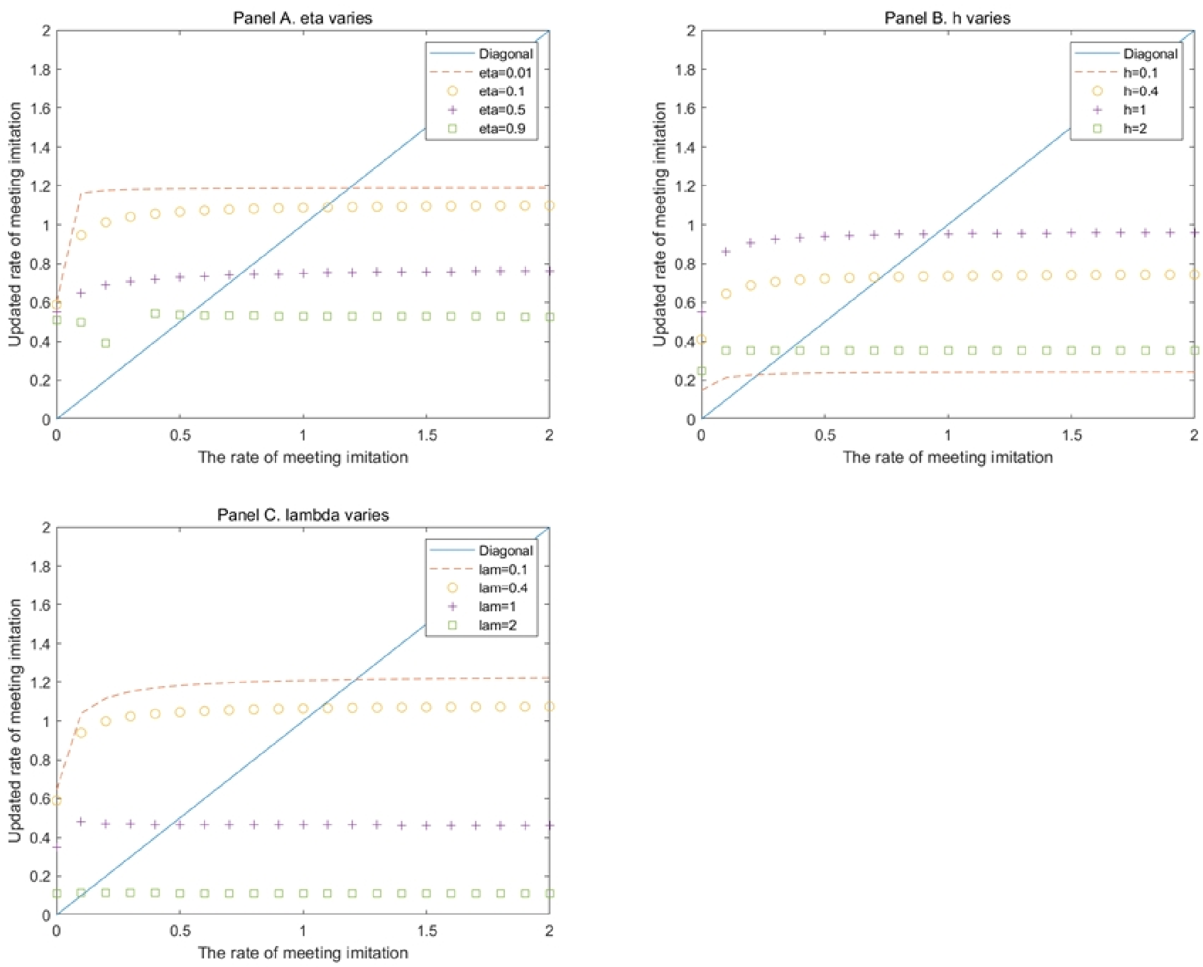
$$\mu^m = \eta P^H_\eta + h \frac{(\mu^I)^2}{(\mu^I + \mu^m)(\mu^I)}. \tag{C.13}$$

Combining these two equations, we obtain

$$\mu^I - \frac{\lambda}{h}\mu^m = \eta P^I_\eta - \frac{\lambda}{P^H h}\eta P^H_\eta.$$

Substituting this into the right-hand side of Equation (C.13), μ^I can be replaced by μ^m. The solution of μ^m can be determined directly. Using the following numerical method, we can check whether the solution satisfies uniqueness and existence for each given (λ, h, P^I_η). We set the benchmark as $(\eta, \lambda, h, P^I_\eta)$=($0.1$, 0.2, 0.6, 0.5). We vary the value of these parameters and numerically check whether the equilibrium has a unique solution. As Figure C.1 shows, there is always a unique solution because of the unique interaction point between the 45-degree line and the curve.

Figure C.1: Uniqueness and Existence of the Equilibrium



Notes: The X axis denotes all possible values of μ^m, and the Y axis value of the curves denotes the updated μ^m based on the RHS of Equation (C.13).

C.7 Empirical Evidence on Profitability and Technology Adoption

In this section, we present an empirical analysis to examine the negative impacts of adopters' productivity and the number of adopters on technology leaders' profitability within each city-industry pair.[41] We define technology leaders as firms in the top 10% of productivity. To measure the extensive margin of competition, we count the number of firms that has no R&D records in each city-industry pair as the number of adopters. In addition, we calculate

[41] An industry is defined at the four-digit level of the Chinese Industry Classification (CIC) code.

the average productivity of competing firms within the same city-industry pair. We expect that both the number of adopters and the productivity of competitors will have a negative effect on profit measures. The results are reported in Table C.2.

Table C.2: Profit and Technology Adoption

	log(Firm Profit)		log(Lerner index)	
log(# Adopter)	-0.26***	-0.19***	-0.08***	-0.04***
	(0.004)	(0.007)	(0.005)	(0.008)
log(Competitor TFP)	-0.11***	-0.08***	-0.31***	-0.16***
	(0.021)	(0.04)	(0.03)	(0.05)
Year	NO	Yes	NO	Yes
City	NO	Yes	NO	Yes
Industry	NO	Yes	NO	Yes
R^2	0.05	0.07	0.013	0.13
Obs	81,878	81,878	81,878	81,878

Notes: OLS. Coefficient p-values are: $^{*}p < 0.10$,** $p < 0.05$,*** $p < 0.01$.

D Appendix to Estimation

D.1 Estimation Procedure

D.1.1 Step 1. Generating firm decisions, aggregate shocks and market structure distribution

The inputs of the economic system are exogenous parameters, which govern the discounted utility, the shape of cost functions, technology upgrade size, discrete choices and entry costs. With these parameters and states that are exogenous to individual firms, firms make dynamic decisions, and the aggregation of these decisions transforms them into exogenous shocks to individual firms.

The explanations for the parameters are given in Table 3. With the given initializing parameters $\{\gamma_1^I, \gamma_2^I, \gamma_1^H, \gamma_2^H, \theta, q, \rho, F\}$, we solve for firm decisions and the corresponding aggregate shocks. First, we use the backward iteration of the value function because this is a dynamic model. Note that Equation (4) provides a method to decompose firm dynamics into product dynamics. Therefore, we do not have to solve for heterogeneous firm decisions; instead, we discuss how firm decisions are made based on each product status independently. There are $1 + 2n^{max}$ value functions to be estimated, of which one is for innovative products without infringement, there are n^{max} states for innovative products suffering infringement, and there are n^{max} states for imitating products. The backward method begins on the last day. Firms do not survive to the next day and earn profits on the last day. On the last day, they only produce and do not make decisions for the future. With the definition of the last day, the infinite dynamic model becomes finite. One day earlier, every product generates profits, and firms make innovation decisions, and technology adoption decisions based on the known future product statues. Furthermore, the aggregate destruction rate and the infringement rate need to be calculated. FOCs help solve firm decisions $\{h, \lambda\}$. To solve for the aggregate variables $\{\mu^I, \mu^m, M(n)\}$, equations (11), (13) and (15) are used. Having solved for firms' decisions and the corresponding aggregate rates, we solve for the value of each type of product one day earlier. This step is repeated until the values converge. Then, the decisions, shocks and market structure distribution, $\{\lambda, h, \mu^I, \mu^m, M(n)\}$, on the BGP are obtained.

D.1.2 Step 2. Simulation

Now, we have firm decisions $\{\lambda, h\}$, the market structure distribution $\{M(n)\}$ and shocks $\{\mu^I, \mu^m\}$. We assume that the number of entrants in one year is $x = 1000$. Moreover, one year is defined as 100 days, so that the time interval $d = 0.01$. On each date, the number of potential entrants is $x = 10$. We use an ID generator to obtain firm IDs to identify entrants, which are used for the entrant's entire life.

The state of a firm's product is (κ, n). The first state variable κ represents the method to obtain knowledge capital, $\kappa \in \{innovation, adoption\}$, and the second state variable n indicates the structure of the market where the firm's product is located, $n \in \{0, 1, ..., n_{max}\}$. The number of all product markets is $p^{max} \equiv \frac{x}{\eta P^I_\eta}$, where ηP^I_η denotes the measure of innovating entrants. An array with p^{max} elements is generated to simulate all product markets. An element in the array is one product market, which records the IDs and knowledge sources of those firms that are active in this market.

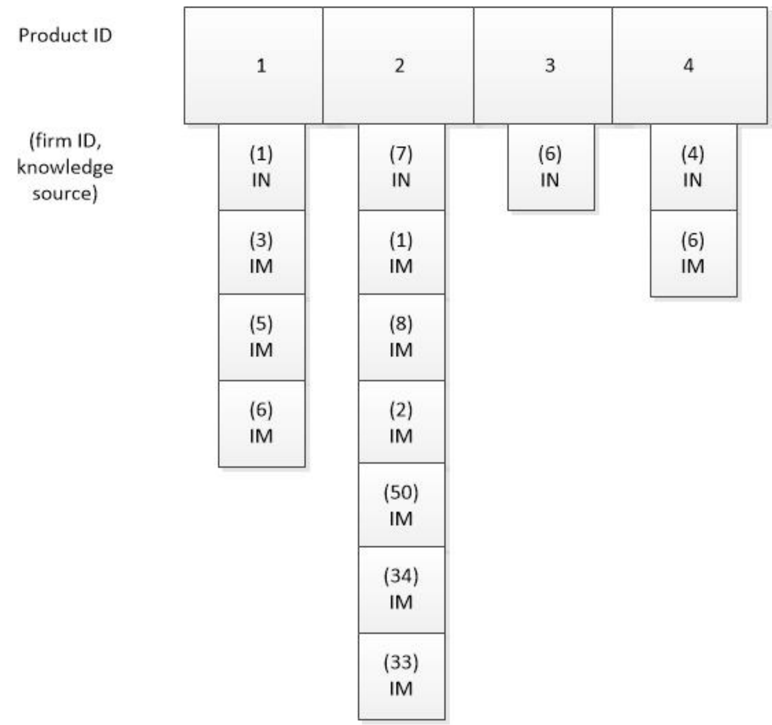
A product market is composed of its active participants, $market \equiv (ID_0, ID_1, ID_2, ..., ID_n)$. The knowledge source is indicated by the order of IDs. The first ID, ID_0, is the innovator, and the other IDs denote adopters. The whole economy is composed of all markets, $\{market_1, market_2, ..., market_{p^{max}}\}$. A simple example is described in Figure D.1. The ID of a product market is p with $0 < p \leq p^{max}$.

For each entrant, we generate a uniform random variable $u^I_{ent} \in (0, 1)$. If $u^I_{ent} < P^I_\eta$, then the entrant obtains the first technology through innovation; otherwise, it chooses technology adoption.

For all markets, we use a uniform random variable $\tilde{u}$ to generate random numbers for each product. The value of the number determines the method of acquiring new technology: If $\tilde{u} < \lambda d$, then the firm uses the knowledge capital of the product to innovate; if $\lambda d < \tilde{u} < \lambda d + hd$, then the firm uses the knowledge to expand a new product through technology adoption; and, otherwise, the firm does nothing.

Each market consists of innovators and adopters. Now, we introduce how the market is formed. For each newly innovative product, we randomly assign it a product market, and then it destroys the existing product market. The number of competitors in the market becomes zero. The first firm ID in the market becomes the innovator's ID, such as the firm IDs 1, 7, 6, 4 in the first row in Figure D.1. For the newly adopted product, we randomly assign a market for the product and add the adopting firm ID to the tail of the existing ID array of participants. As a result, the number of competitors in the markets increases by one, including the firm IDs 6, 33, 6 in the markets 1, 2 and 4, respectively.

Figure D.1: A simple example of the state of an economy

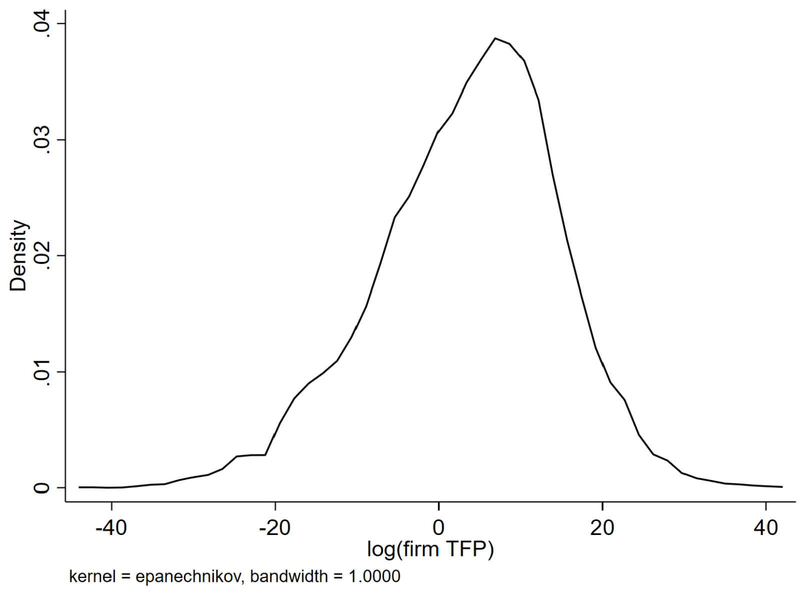


Notes: This figure shows a simple example of an economy with only four product markets. The product IDs for the four markets are 1, 2, 3 and 4. For each market, there is one innovator and several technology adopters. For example, in the first market, there is one innovator and three adopters. The firm ID for the innovator is 1. The firm IDs for the adopters are 3, 5 and 6. IN and IM are short for innovation and adoption, respectively, which imply the knowledge capital source.

D.2 Simulated Distribution of Productivity

We also present the simulated distribution of firm productivity at a selected date along the BGP. The results are shown in Figure D.2. Although our model does not specifically target the moments of productivity in the model fitting, the simulated distribution exhibits favorable characteristics. The simulated distribution aligns with the key features targeted by König et al. (2016), that also model innovation and adoption together. Specifically, both high-productivity and low-productivity firms follow power laws, and the distribution shifts consistently over time in an affine manner.

Figure D.2: Simulated distribution of firm productivity



Notes: To obtain the firm productivity in the model, we completed the following procedures. First, we collected the upgrade times κ^j for each product j in the simulation. In addition, we collected l_i^j, the number of labor units used to produce product j by firm i. Second, we calculated the quality or productivity of each product by $logTFP^j = \kappa^j log(q)$. Third, we calculated the physical output (adjusted by quality) for each firm-product pair $logQ_i^j = logTFP^j + log(l_i^j)$. Finally, we obtained the firm productivity by $log(TFP_i) = log(Q_i) - log(l_i)$, where Q_i and l_i are the aggregate output and input in production by firm i, respectively.

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