Patent Protection in Developing Economies: The Role of Market Power and Technology Access *

Weili Chen †
Penn State

This Version: November 10, 2024

[PLEASE ACCESS THE LATEST VERSION HERE]

Abstract

This paper examines the trade-off between market power and access to advanced technologies in the context of patent protection policy in developing economies. I exploit a policy shock in China that unevenly strengthened patent enforcement across provinces, combining it with a novel dataset that links Chinese firm-level production data to multinational firms' global patent portfolios. I find that stronger patent protection incentivizes multinational firms to adopt their best technologies in Chinese affiliates and encourages domestic inventors to produce higher-quality innovations. However, both groups also increase their markups. To rationalize and quantify these findings, I develop a multi-product model where inventors endogenously reduce markups but withhold higher-quality products due to concerns over local imitation. Enhanced patent enforcement expels imitators, prompting inventors to adopt superior products while raising markups across their portfolios. The calibrated model reveals an inverted U-shaped relationship between patent protection and aggregate welfare, with strong heterogeneity across industries.

JEL Classification: F12, F23, L11, O34

*I am deeply grateful to my advisors, Stephen Yeaple, Jingting Fan, and Mark Roberts for their continued guidance and generous support. I thank David Atkin, Jie Bai, Yan Bai, Maria-Jose Carreras-Valle, Thomas Chaney, Robin Gong, Gordon Hanson, David Hémous, Kala Krishna, Vijay Krishna, Edwin Lai, Ernest Liu, Jin Liu, Paolo Martellini, Marc Melitz, Eduardo Morales, Fernando Parro, Michael Peters, Bernardo Ribeiro, Conor Ryan, Bradley Setzler, James Tybout, Jose Vasquez, Zi Wang, Kai-Jie Wu, Wei Xiang, Daniel Xu for very helpful conversations, and participants of numerous seminars and conferences for their comments. All errors are mine.

†Ph.D. Candidate, Department of Economics, Pennsylvania State University. Email: weilichen-econ@psu.edu.

1 Introduction

Over the past decades, intellectual property rights (IPRs) have moved from a niche legal issue to the forefront of global economic policymaking. The enhancement of patent protection is especially pronounced in developing economies. As net importers of advanced technologies, developing countries have been compelled to strengthen their protection standards in line with WTO requirements. The economic impacts of these policy changes remain obscure, and quantitative studies on their effects are scarce.

Patent protection presents policy makers in developing countries with a dilemma. On the one hand, insufficient protection not only discourages domestic innovation but also deters multinational enterprises (MNEs) from transferring their best technologies, limiting the assimilation of advanced technologies from developed nations.[1] On the other hand, excessive protection grants market power to patent-holding firms, resulting in higher prices for consumers and an outflow of profits abroad. Achieving this balance requires insight into how markups and technology adoption respond to varying levels of patent protection.

This paper empirically and quantitatively examines this policy dilemma in the context of China following its WTO accession. It makes two contributions. First, exploiting a policy shock that unevenly strengthened patent enforcement across Chinese provinces, I provide new causal evidence showing simultaneous increases in technology adoption and markups in response to stronger patent protection. Within-firm selection of top-quality technologies (measured by patent citations) emerges as a key driver of this increase in technology adoption. Second, I develop and calibrate a model to microfound the link between patent infringement and firms' decisions on markups and technology adoption, allowing for a quantitative assessment of the welfare impact of patent protection. I find that the relationship between welfare and patent protection features an inverted U-shape, with the 2004 enhancement proving welfare-improving but falling short of the optimal level. Model-based decomposition confirms that the within-firm selection of top-quality technologies is quantitatively important, contributing twice as much to welfare gains as firm-level entry.

The first contribution of this paper is empirical. Identifying the causal impacts of patent protection has long been challenging, as patent policy changes often coincide with other reforms, and patent protection measures are often correlated with broader economic indicators. I utilize a quasi-experiment in China, where provincial variation in patent *enforcement* allows for causal identification of these impacts. In December 2004, the Chinese central government launched a special campaign to improve IPR enforcement. Nine provinces were selected for a crackdown on the infringement of invention patents, with inspection teams from the central

[1] Ample anecdotal and survey evidence support this point. Branstetter, Fisman and Foley (2006) document that the leading semiconductor manufacturer, Taiwan Semiconductor Manufacturing Co. (TSMC), had not transferred its most advanced technology to its affiliate in mainland China, anticipating that its patents would be infringed by domestic firms. This paper provides the first systematic evidence to validate this hypothesis.

government dispatched to provincial levels to expel local firms infringing on others' patents. The exit rate of Chinese firms without patents surged immediately following the campaign in these treated provinces, a pattern that is not observed among foreign affiliates and Chinese firms with patents.

To examine how the exit of potential patent-infringing firms affects the behaviors of patent holders, I construct a new dataset of firm-level production and patenting. My dataset links the Chinese firm-level manufacturing survey data to the patent data from PATSTAT Global and Orbis Intellectual Property (Fan, 2024). For each firm, I track its historical patent records and measure the quality of each patent based on the number of future citations. Importantly, for each foreign affiliate, I establish a link to the global patent portfolio of its headquarters, allowing me to observe the patented countries of each *patent family*, which typically protects one product or one piece of production technology invented by the multinationals.

I document three novel findings. Firstly, strengthened local patent enforcement increases multinationals' willingness to adopt their technologies in their Chinese affiliates, and this increase is solely concentrated in their top-quality technologies (i.e., patents that are most highly cited). I measure the willingness of adoption by examining the propensity to seek patent protection in China for technologies patented in other countries by the multinational firm. For a typical multinational firm with its affiliate located in the treated provinces, the share of its top 10% quality inventions seeking patent protection in China increases by 15 percentage points. In contrast, the patenting rate in China for inventions of lower quality remains unchanged. This finding corroborates anecdotal evidence that multinationals are hesitant to transfer their best technologies when patent protection is weak, underscoring the within-firm selection of top-quality technologies in response to changes in patent protection.

Secondly, better patent protection also stimulates domestic innovation. Compared to other locations, the probability of a Chinese firm inventing a new patent in the treated provinces increases by around 2 percentage points. These patents tend to receive more citations and are more likely to be granted in the U.S., Europe, or Japan. This finding suggests that stronger patent enforcement not only encourages domestic firms to innovate more but also enhances the quality and international recognition of their inventions.

Thirdly, strengthened patent protection induces patent holders to raise their markups. I estimate firm-level markups with production function estimation. Using a triple-diff-in-diff specification, I find that multinational affiliates and Chinese patent holders in treated provinces both increase their markups by about 2 percentage points compared to domestic firms without patents in the same province-industry. Since patent protection primarily benefits firms with patents, domestic firms without patents serve as a control group to capture equilibrium impacts, allowing for a causal interpretation of intensified patent enforcement's effects on the markup responses of patent holders.

Together, my empirical findings show that patent protection improves technology access by attracting cutting-edge technologies, both through multinationals adopting existing technologies and domestic firms introducing new inventions. However, this enhanced access comes at a social cost, as stronger patent protection also induces patent holders to raise markups. Quantitatively assessing the aggregate impact of patent protection, therefore, requires a framework to disentangle these mechanisms.

The second contribution of this paper is to develop a model that incorporates essential mechanisms to explain the empirical findings and quantify their aggregate impacts. In the model, heterogeneous inventors with technologies from home or abroad are each endowed with a portfolio of products that vary in quality. Higher-quality products are more valuable to consumers but entail greater costs of invention. For domestic firms, product invention represents genuine innovation, while for foreign firms, it reflects the adoption of technology from headquarters to production affiliates. Upon introducing the product, the inventor holds the patent that specifically covers the technology to produce it at its quality level.

The model provides a new micro-foundation for patent infringement activities. I model patent infringement as imitators producing distinct varieties of a patented product. From a consumer's perspective, these imitator-produced varieties are closer substitutes for the original variety than products covered by other patents. This feature is captured through a nested CES preference structure similar to Atkeson and Burstein (2008), which allows for variation in the markup charged by the patent holder, depending on its market share relative to the imitators who infringe on this patent.

When patent protection is imperfect, the model highlights a new feature where inventors self-select to adopt only their lower-quality products, leaving their top-quality products out of the market. While this feature aligns with our intuition and anecdotal evidence on patent protection, it contrasts with conventional theories of selection driven by fixed costs (e.g., Melitz, 2003; Bernard, Redding and Schott, 2011), where typically advanced technologies enter the market and backward technologies exit. This outcome stems from the model's endogenous imitation, where imitators select themselves to target higher-quality patents. Consequently, high-quality products face tougher imitation, resulting in a larger decline in profitability for inventors. Anticipating these profit losses, inventors optimally withhold their top-quality products when the profits no longer cover the fixed invention costs.

Patent enforcement plays a crucial role by reducing the probability for imitators to secure profits, thereby deterring their entry. Strengthened patent enforcement reduces competition from imitators, inducing inventors to simultaneously increase their markups on the existing product portfolio and introduce their higher-quality products. The overall welfare implications of intensified patent enforcement, therefore, depend on the aggregation of such within-firm trade-off between markups and product scope, together with the firm-level entry and exit driven by the aggregate competition.

To quantitatively access the aggregate impact of patent protection, I calibrate the model using Chinese firm-level data in 2004, before the IPR enhancement campaign. I parameterize and discipline the distributions of product quality and firm heterogeneity to match the observed distributions of patent quality, patent entry rates and firms' sales.

I apply the calibrated model to quantify the aggregate impacts of patent protection. I find that the 2004 IPR enhancement campaign in China was welfare-improving, with an increase in aggregate real income by 0.83%. The sensitivity of markups and technology adoption to patent protection varies by industry. For instance, Chemicals and Electrical Equipment see gains from the introduction of top-quality products, particularly by foreign firms, while Pharmaceuticals and Electronics experience price inflation as both Chinese and foreign firms raise markups.

The model enables a decomposition of welfare changes into different mechanisms: the loss from increased markups on incumbent products, the gain from the entry of top-quality products, and the adjustments at the firm-level extensive margin. Notably, the within-firm adjustments by incumbents have approximately twice the impact of firm-level entry and exit, underscoring the importance of the previous empirical findings on within-firm changes in technology adoption and markups.

To further evaluate the optimality of patent policy, I conduct a counterfactual analysis by varying the level of patent enforcement, revealing that the aggregate impact on real income follows an inverted U-shape. Compared to the status quo, the optimal enforcement level, which is stronger than that of the 2004 IPR campaign, would yield approximately 0.93% in welfare gains, while full protection is sub-optimal, yielding only a 0.5% increase.

Related Literature. This paper contributes to the long-lasting debate of intellectual property rights (IPR) protection in developing economics. Existing studies have documented that IPR reforms in developing countries lead to more technology transfer from MNE headquarters (Branstetter et al., 2006) and more multinational activities (Bilir, 2014), increased imports of high-tech goods (Ivus, 2010), improved financing and R&D investment (Ang, Cheng and Wu, 2014), and other domestic industrial development (Branstetter, Fisman, Foley and Saggi, 2011; Lai, Maskus and Yang, 2020). My paper contributes to this literature by providing a new measure of technology adoption using patent entry, and causal evidence documenting simultaneous increases in technology adoption and markups. I also highlight the within-firm selection of top-quality technologies as an important contributor to the increase in adoption, thereby showing how patent protection shapes the quality of technology access.

Most existing empirical studies rely on externally constructed indexes as proxies for IPR protection strength (e.g., Ginarte and Park, 1997; Park, 2008; Ang et al., 2014; Lai et al., 2020). These index-based measures of patent protection are often constructed by aggregating different statistics on institutional or judicial quality.[2] However, these statistics are likely correlated with

[2]The widely used Ginarte-Park index measures the strength of patent protection in each country by scoring its judicial system over five broad categories: (1) membership in international IPR treaties, (2) extent of technology coverage, (3) duration of protection, (4) limitations on patent breadth (e.g., compulsory licensing), and (5) legal

broader institutional or economic changes, complicating causal identification of patent protection and limiting their use in a quantitative structural framework. Unlike previous work, I identify the causal effects of patent protection by examining a policy shock, using an event study that exploits both provincial-level variation in patent enforcement and firm-level variation in ownership and patenting behavior.[3]

While numerous theories have explored the impacts of IPR in the open economy (e.g., Lai, 1998; Yang and Maskus, 2001; Grossman and Lai, 2004; Glass and Wu, 2007; Branstetter and Saggi, 2011; Bilir, 2014), quantitative models with IPR protection have been scarce until recently (Santacreu, 2023; Hémous, Lepot, Sampson and Schärer, 2023; Lam, 2024). This paper develops a partial equilibrium model to rationalize the empirical findings and quantify their implications. My model differs from the existing IPR theories in two main aspects. Firstly, it provides a micro-foundation for imitation activities, allowing for variable markups determined endogenously by the entry of imitators. By embedding the market structure of Shimomura and Thisse (2012) into the nested CES demand framework by Atkeson and Burstein (2008), the model captures extensive-margin variations of imitators while maintaining tractability. Secondly, previous theories mainly focus on firm-level outcomes and do not account for within-firm adjustments—a margin I find to be more important both empirically and quantitatively in explaining the impact of patent protection.

This paper also adds to the broader discussion on China's industrial policies aimed at fostering technology access. A vast body of work evaluates the effectiveness of R&D policies on domestic innovation in China (e.g., Ding and Li, 2015; Chen, Liu, Suárez Serrato and Xu, 2021; König, Storesletten, Song and Zilibotti, 2022), while an emerging literature examines the impacts of government-initiated programs to increase international technology transfer through policies such as *quid pro quo* (Holmes, McGrattan and Prescott, 2015; Bai, Barwick, Cao and Li, 2023; Ma and Zhang, 2024). This paper sheds light on the role of patent protection as a policy tool to foster technology access, through both domestic innovation and foreign transfer, and it also discusses the costs of such policies arising from increased market power.

The rest of this paper is organized as follows. Section 2 introduces the data and the institutional background of the policy shock. Section 3 presents the empirical evidence and motivates the model. Section 4 builds the model, which is then calibrated to data in Section 5. Section 6 provides the quantitative analyses. Section 7 concludes.

enforcement mechanisms. Ang et al. (2014) and Lai et al. (2020) construct provincial-level indexes in China based on the winning rate of plaintiffs in patent infringement cases, the number of news articles emphasizing IP protection, or the ratio of settled patent disputes to cumulative granted patents.

[3]One related paper in this context is Qian (2008), which studies another policy shock in China where trademark enforcement was reduced in the footwear industry, showing that the massive entry of counterfeiters induces authentic brands to invest in differentiating technologies and self-enforcement of trademark protection to escape competition from counterfeiters. Her focus is on trademark, while my focus is on patents.

2 Data and Institutional Background

2.1 Data Sources and Measurement

I assemble a dataset focusing on the production and patenting activities of manufacturing firms in China, which includes domestic Chinese firms and multinational enterprises (MNEs) with production affiliates in China. This subsection outlines the main data sources and the merging procedures, with further details provided in Appendix A.

Production Data. The analysis centers on Chinese manufacturing firms in the Annual Survey of Industrial Enterprise, maintained by the National Bureau of Statistics of China (NBSC). This dataset covers all state-owned enterprises and non-state-owned firms with annual sales exceeding 5 million RMB from 1998 to 2007. It provides comprehensive accounting and production information, including firm identity, ownership, location, main industry classification, revenue, employment, fixed assets, and expenditure on intermediate inputs.

To maintain consistent firm identification over time, I implement a procedure following Brandt et al. (2017) to generate a unique identifier. During the period, the majority of firms in the dataset operate as single-plant entities within a single province and primarily engage in one main industry. Throughout the paper, I focus on patent-intensive industries, defined as those industries with above-median number of total patents per employment (Blank et al., 2012), as detailed in Appendix A.2. These industries encompass over half of the firms in the original data. The final dataset constitutes an unbalanced panel spanning 2002–2007, with the number of firms increasing from 155,928 in 2002 to 167,093 in 2007.

Patent Data. I obtain patent data from two primary sources and merge with the NBSC production data. Figure 1 provides an illustrative example for how data from different sources are merged. First, I merge the NBSC data with patent data from China's State Intellectual Property Office (SIPO) by matching the firm's name with the name of the patent applicant. This step provides the unique patent identifier for all the patents filed during the sample period (e.g., patents 1 and 3 in Figure 1). Second, using the unique patent identifier provided in the SIPO data, I link to detailed patent information in PATSTAT (European Patent Office, 2023), which includes records of the forward citations each patent received up to 2023.[4] Additionally, using the applicant information in PATSTAT, I am able to trace the historical patents filed by each firm (e.g., patents 2 and 4 in Figure 1), which are missing in the SIPO data. Together, this approach enables me to comprehensively observe the annual number of patents filed by each firm in the NBSC dataset from 1980 onwards, as well as the forward citations received by each patent.

Following established methodologies in the literature (e.g., Bryan and Williams, 2021), I

[4]Appendix A.1 provides detailed information on the methodology used to link these data sources. This process involves careful investigation of changes in China's patent application numbering system between different vintages.

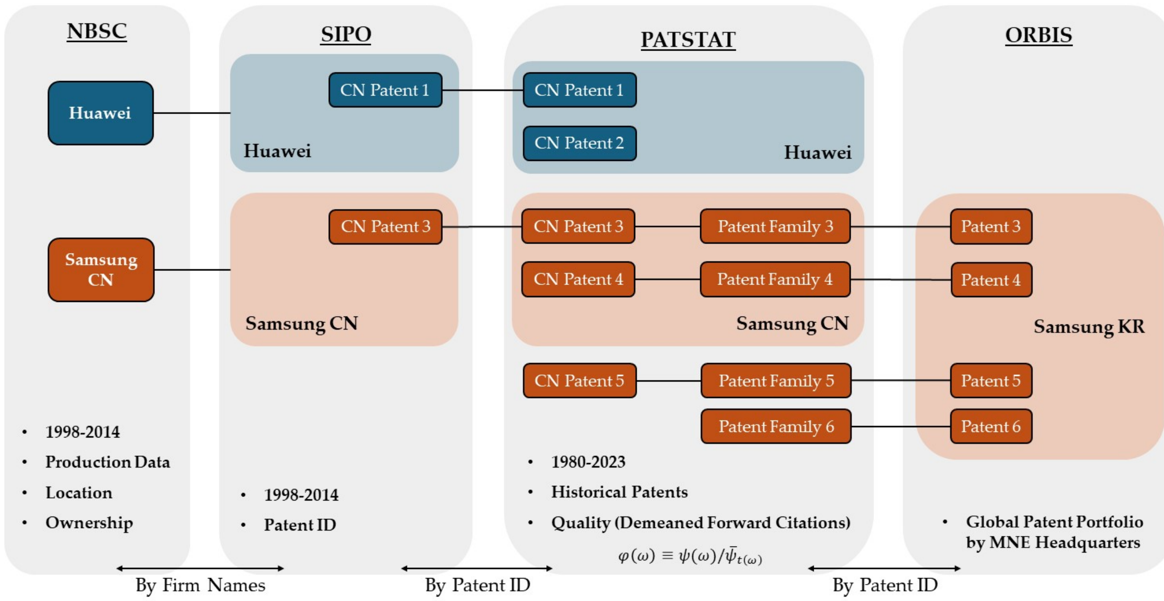


Figure 1: An Illustrative Example for Dataset Construction

Notes: This figure outlines the data sources and the construction of the final dataset. The primary data source is Chinese manufacturing production data from the National Bureau of Statistics of China (NBSC), which I merge with Chinese patent data from the State Intellectual Property Office (SIPO) by matching firm names. Using unique patent application identifiers, I then link this with PATSTAT to obtain further details (e.g., citation data) and historical patents filed by the same firm. Finally, I integrate global patent portfolios of MNEs from the Orbis Intellectual Property Database with PATSTAT by matching patent identifiers. Here, Patent 1 includes patents filed by Chinese firms found in both SIPO and PATSTAT, while Patent 2 includes those missing in SIPO. Similarly, Patents 3 and 4 represent patents filed by foreign affiliates in China, with Patent 3 appearing in both SIPO and PATSTAT, and Patent 4 missing in SIPO. Patent 5 includes patent families invented by headquarters that have a Chinese patent, while Patent 6 represents those without a Chinese patent.

use forward citations as a proxy for patent quality. Specifically, for a patent ω invented in year $t(\omega)$ and receiving forward citations $\psi(\omega)$, its quality is defined as $\varphi(\omega) \equiv \psi(\omega)/\bar{\psi}_{t(\omega)}$, where $\bar{\psi}_{t(\omega)}$ represents the average number of citations received by all patents globally invented in the same year. This adjustment accounts for the trend that more recent patents tend to receive fewer citations, thus enabling inter-temporal comparisons.

Global Patent Portfolio of MNEs. To investigate how multinational enterprises (MNEs) adjust their patenting strategies in China in response to local patent protection, I further merge the NBSC data with information from the Orbis Intellectual Property Database, as used in Fan (2024). To my knowledge, this paper is the first to integrate these two databases. This integration links foreign affiliates in China with the patenting behaviors of their respective headquarters, providing a unique opportunity to examine the global patent portfolios and the willingness of MNEs to adopt technologies in their Chinese affiliates.

As shown in Figure 1, the two datasets are merged using patent identifiers. First, each MNE patent in Orbis is linked to its patent family in PATSTAT. Each patent family consists of applications filed across different patent offices, typically covering a single product or technology.

Second, I match the Chinese patents filed by MNE affiliates from the NBSC data to their respective patent families (e.g., patents 3 and 4), establishing a link between the foreign affiliate in China and its global headquarters. This process allows me to define the global patent portfolio of the multinational firm as the set of technologies potentially available for adoption by the Chinese affiliate. Note that some patents, filed by the headquarters or other affiliates of the MNE, may be patented in China (e.g., patent 5) but not owned by the Chinese affiliate. These patents protect products or technologies that can still be adopted by the Chinese affiliates and are covered under China's patent law. In constrast, there are patents (e.g., patent 6) that have no Chinese application, meaning that the sales and production of these products and technologies are not protected in China.

Measuring Willingness of Technology Adoption. The measurement of an MNE's willingness to adopt its technology in its Chinese affiliate hinges critically on the last type of patents (e.g., patent 6), namely those patented in other countries but not in China. Conditional on patenting elsewhere, the cost of filing an additional application in China is not substantial. However, without a Chinese patent, the production of the corresponding products and technologies is not protected under China's patent law. Therefore, whether each patent family includes a patent application filed in China serves as an ideal measure of an MNE's commitment to the Chinese market by securing local patent protection—if a technology is not patented in China, it is highly unlikely to be utilized by its Chinese affiliate.[5]

For better illustration, consider an example of Samsung Electronics, a major South Korean company with manufacturing sites globally, including in the U.S., Europe, and China. In 2006, Samsung developed a technology for an "LED package with Diffusing Material" and patented it in Korea (KR100665222), the U.S., the European Patent Office (EPO), Japan, and China. This patent, holding the second-most forward citations among all its patents from 2006, has a quality index of $\varphi(\text{LED}) \approx 35$. The most cited patent from the same year was for "Organic Light Emitting Display (OLED)," a presumably more cutting-edge technology at the time, with a quality index of $\varphi(\text{OLED}) \approx 164$. However, this OLED patent was only registered in Korea (KR100711890), the U.S., and the EPO, but notably *not in China*. To my knowledge, Samsung produced LCD screens at its Chinese affiliate but had no OLED production line at the time. If Samsung had adopted its OLED production technology in China, it would likely have applied for a Chinese patent to secure protection. In Section 3.2, I investigate how the propensity of MNEs to patent in China changes in response to strengthened patent enforcement to identify the impact of patent protection on MNEs' willingness to adopt their technologies with various quality.

[5] It is also crucial to note that patent institutions require all international patent applications from a patent family to be filed within 12 months of the first application (typically through PCT or Paris Convention). Thus, if an MNE intends to seek patent protection for this technology in China eventually, it must file for a Chinese patent when the technology is first developed.

Table 1: Firm Number and Market Share in Year 2004

	Firm Number		Market Share	
	Without Patent	With Patent	Without Patent	With Patent
Domestic	131,600 (76.2%)	5,688 (3.3%)	36.8%	23.5%
Foreign	33,319 (19.3%)	2,128 (1.2%)	27.3%	12.4%

Notes: This table presents firm numbers and market shares categorized by domestic and foreign entities, considering whether they hold a patent. Foreign firms are defined as entities registered as joint ventures or wholly foreign-owned, with ownership from Hong Kong, Macao, Taiwan (HMT), or other foreign countries. A patent holder is identified as a firm that has filed at least one invention patent since 1990. This designation considers the 20-year validity period of an invention patent in China.

Summary Statistics. Table 1 provides an overview of firm numbers and market shares in 2004, distinguishing between domestic and foreign firms, with and without patents. Notably, although foreign firms make up approximately 20% of the total number of firms, they command about 40% of the market share. Furthermore, an important characteristic of patent-intensive industries emerges: patent holders, while small in number—constituting less than 5% of firms—hold a disproportionately large market share of over 30%. This substantial market presence highlights the advantages enjoyed by patent holders, and motivates my subsequent modeling of the market structure, whereby large patent holders compete with a multitude of smaller imitators.

2.2 The IPR Enhancement Campaign in China

In December 2004, the Chinese central government initiated a special campaign aimed at enhancing Intellectual Property Rights (IPR) protection nationwide, perhaps strategically timed prior to then Chinese President Hu's visit to the United States in September 2005. This campaign served as a signal to the international society regarding China's commitment to a strong IPR regime. It marked the government-led effort focused on the actual *enforcement* of IPR laws and was perceived as a successful crackdown on IPR infringement. Given that the campaign was centrally initiated and announced merely four months before its implementation, the shock was unanticipated to individual firms, and the treatment was relatively uniform across the provinces targeted for intervention.

According to a government report, a national working group dedicated to enforcing IPR was established during this campaign. In particular, nine provinces were selected for a special crackdown on the infringement of invention patents.[6] Inspection teams were dispatched

[6] China's IPR system covers a range of protections for various types of intellectual property, including patents (covering inventions, utility models, and designs), trademarks, copyrights, trade secrets, and more. For the purposes of this paper, I specifically focus on the protection of invention patents. The nine provinces selected to enhance the protection of invention patents are Shanghai, Beijing, Jiangsu, Guangdong, Liaoning, Jilin, Heilongjiang, Hubei,

from the central government to provincial levels to combat patent infringement activities. Consequently, a substantial number of firms found infringing on others' patents were effectively removed from the market. In the following subsections, I leverage this treatment to study the impacts of patent enhancement on technology allocation and markups of inventors.

3 Empirical Evidence

In this section, I present the main empirical findings on the impacts of strengthened patent enforcement. I begin by validating the effectiveness of the policy shock, showing that the exit rate of potential imitators increased sharply in the intervened provinces relative to those untreated. I then document the patenting and markup responses of MNEs and domestic inventors when competition from imitators is suppressed due to intensified patent enforcement. First, I show that MNEs are more likely to seek patent protection in China for their globally invented technologies, and that this increase is concentrated in technologies with the highest quality. Next, I document that domestic Chinese firms are more likely to introduce new inventions of higher quality than their existing patent portfolios. Finally, both MNE affiliates and Chinese patent holders increase their markups in response to strengthened patent protection.

3.1 Validating Policy Shock: Exit of Imitators

To assess the effectiveness of the campaign, I investigate changes in the exit rate of different groups of firms using the following specification:

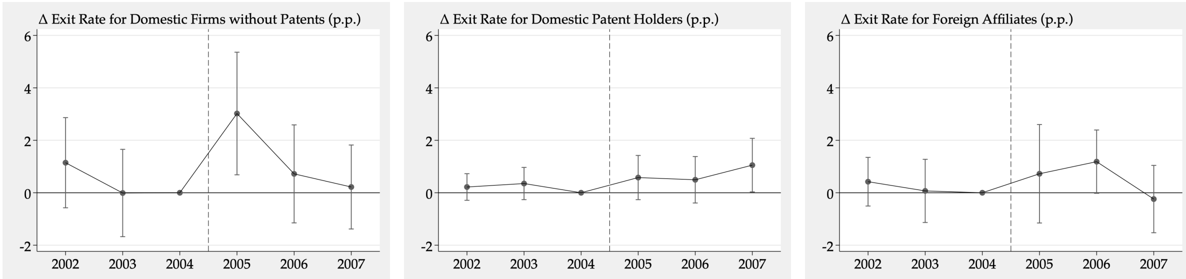
$$\mathbb{I}\left[f \text{ exits in } t\right] = \sum_{\tau \neq 2004} \beta_\tau \cdot \mathbb{I}\left[l(f) \text{ is treated}\right] \cdot \mathbb{I}\left[t = \tau\right] + X_{l(f)t} + FE_f + FE_{j(f)t} + \varepsilon_{ft} \quad (1)$$

where $\mathbb{I}\left[f \text{ exits in } t\right]$ is a binary variable that takes the value of one when firm f drops out of the sample in year t and does not appear in any subsequent year. $l(f)$ denotes the province where firm f is located, and $j(f)$ denotes the industry in which firm f operates. I control for firm-level fixed effects and industry-year fixed effects, and include the log of province-level GDP in $X_{l(f)t}$ to control for other concurrent policy shocks, with standard errors clustered at the province-year level.

I classify firms in the data into three categories: domestic firms that never file a patent, domestic patent holders, and all foreign firms.[7] It's likely that imitators found infringing on others' patents belong to the first category, while domestic patent holders and foreign firms are

and Shaanxi.

[7] It is generally assumed that most foreign affiliates in China adopt technologies transferred from abroad. Nonetheless, the patents safeguarding these technologies may not be held by the affiliates themselves but rather by their foreign headquarters. In the dataset, if an affiliate does not file any patents, such patenting records would be absent. Consequently, to simplify the analysis and ensure clearer identification, all foreign affiliates are categorized together regardless of their individual patenting behavior.



(a) Domestic Firms without Patents (b) Domestic Patent Holders (c) Foreign Affiliates

Figure 2: Exit Rate for Different Categories of Firms

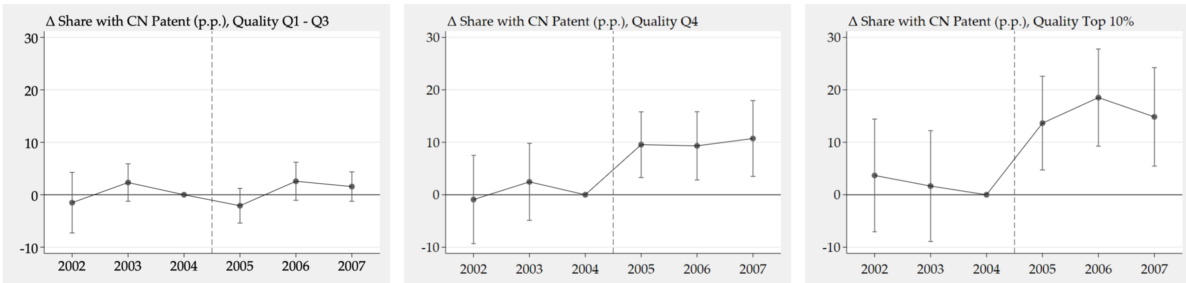
Notes: This figure plots the regression coefficients in (1) for different categories of firms. The dependent variable is the propensity to exit (in percentage point). Fixed effects are controlled for at the firm and industry-year level, with standard errors clustered at the province-year level. Industries are at the level of 2-digit International Standard Industrial Classification (ISIC Rev. 4).

more inclined to produce using self-developed or foreign-transferred technologies. If the IPR campaign was indeed effective, we would anticipate an increase in the exit rate for imitators located in the treated provinces relative to the untreated provinces. However, such patterns should not be observed in the other two categories of firms. This expectation arises from the assumption that the campaign effectively targets firms engaged in patent infringement activities, primarily found among domestic firms that never file a patent. Conversely, domestic patent holders and foreign firms are less likely to engage in such practices, thus not expected to be significantly affected by the campaign in terms of exit rates.

The results reported in Figure 2 confirm this expectation. Relative to the untreated provinces, the exit rate for potential imitators located in the treated province was very similar before 2004, but increased significantly by around 3 percentage points (p.p.) right after the IPR campaign. However, such patterns are not observed for domestic patent holders or foreign firms. This confirms a significant decrease in production by imitators at the extensive margin.

3.2 MNEs Become More Willing to Adopt Their Best Technologies

To investigate how stronger patent protection affects MNEs' willingness to adopt technologies in their Chinese affiliates, I analyze changes in the propensity of MNEs to patent their globally invented technologies in China following the improvement of patent enforcement in the province where their affiliates are located. As illustrated in Section 2.1, given the relatively low patenting costs in China and the institutional requirements for international patent filing, securing a Chinese patent is typically necessary for MNEs transferring technologies to their Chinese affiliates. Therefore, the propensity to apply for a Chinese patent for a globally invented technology serves as a proxy for the willingness to adopt that technology.



(a) Bottom 75% (b) Top 25% (c) Top 10%

Figure 3: Share of Patents with a Chinese Application by Quality

Notes: This figure examines how enhanced patent enforcement affects MNEs' willingness to adopt technologies in China. The plots present the regression coefficients in (2) for different percentiles of patent quality. The dependent variable is the share (in p.p.) of patent families invented globally that has a Chinese patent. Fixed effects are controlled for at the firm and industry-year level, with standard errors clustered at the province-year level. Industries are at the level of 2-digit International Standard Industrial Classification (ISIC Rev. 4). Regression details are reported in Table A.2.

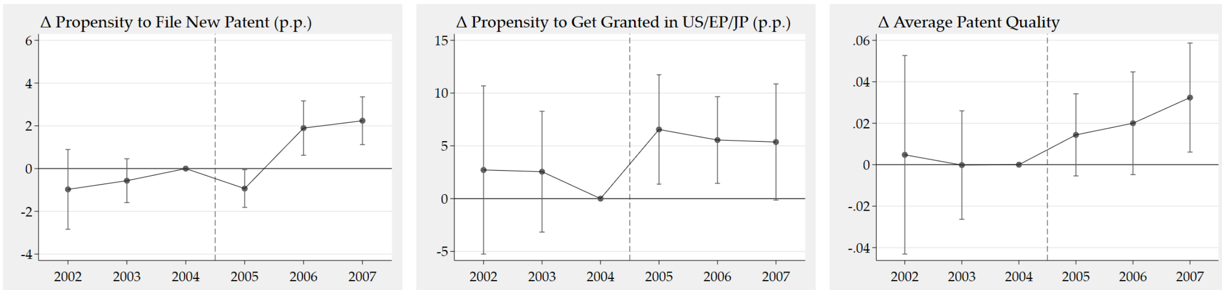
Building on this insight, I perform the following event study:

$$\mathcal{S}_{ft} = \sum_{\tau \neq 2004} \beta_\tau \cdot \mathbb{I}\left[l(f) \text{ is treated}\right] \cdot \mathbb{I}\left[t = \tau\right] + X_{ft} + FE_f + FE_{j(f)t} + \varepsilon_{ft}, \tag{2}$$

where $\mathcal{S}_{ft}$ represents the share of patents globally invented by firm f in year t that include a Chinese application. A larger value of $\mathcal{S}_{ft}$ indicates an increased willingness of firm f to deploy its new technologies in China during that year. $l(f)$ denotes the province where firm f is located, and $j(f)$ denotes the industry in which firm f operates. FE_f are firm-level fixed effects that control for factors affecting a firm's overall willingness to patent its technologies in China. $FE_{j(f)t}$ are industry-year fixed effects that account for factors influencing the average tendency of MNEs in industry j to adopt technologies to Chinese affiliates in year t, such as changes in market demand or trade policies. Lastly, X_{ft} represents additional control variables that may affect the propensity of firm f to patent in China during year t, including employment size, patent stock, provincial-level GDP, and a firm-specific time trend.

Figure 3 reports the results. I run the regression with different groups of patents based on their within-firm-year quality rank. The results show that enhanced patent protection does not affect the likelihood of MNEs patenting their inventions of normal quality (i.e., those in the bottom three quartiles). However, it significantly increases the propensity for patents of top-quartile quality. This increase is largely driven by the response of the highest-quality patents, specifically those in the top 10%, as demonstrated in Figure 3c. Quantitatively, the share of top 10% quality inventions seeking patent protection in China increases by 15 p.p. on average. This is a substantial increase, given that the average Chinese patenting rate for these top-quality inventions was only 36% in 2004.

A potential endogeneity concern may arise from the measurement of patent quality. One might argue that the heterogeneous response among patents of different qualities is not due to



(a) Propensity to File a New Patent (b) Granted in US/EP/JP (c) Average Quality of Patent Portfolio

Figure 4: Innovation Activities of Domestic Firms

Notes: This figure examines how enhanced patent enforcement affects domestic firms' innovation activities. The plots present the regression coefficients in (2) with different dependent variables. Fixed effects are controlled for at the firm level and the industry-year level, with standard errors clustered at the province-year level. Industries are at the level of 2-digit International Standard Industrial Classification (ISIC Rev. 4). Regression details are reported in Table A.3.

self-selection but rather due to reverse causality—that is, patents receive more forward citations because they are also patented in China. To mitigate this concern, I exclude all citations from Chinese patents when measuring the quality rank. The results remain robust when Chinese citations are also included.

3.3 Domestic Firms Introduce More Inventions with Higher Quality

In theory, patent protection can facilitate access to technologies not only by fostering foreign technology transfer but also by stimulating domestic innovation. To empirically test the latter hypothesis, I analyze the same specification in (2) with different measures of domestic innovation activities as the dependent variable, restricting samples to domestic firms.

To start with, I assess whether firms in the treated provinces are more likely to file new patents following the enhancement of patent enforcement. Specifically, I define the dependent variable as an indicator that takes the value of one if firm f files an invention patent in year t. The results, displayed in Figure 4a, show that firms in the treated provinces are significantly more likely to introduce new patents after the policy shock compared to those in other provinces, with an increase in propensity by around 2 p.p.

A subsequent inquiry explores whether these newly induced patents are of higher or similar quality compared to the existing patent portfolio. Figure 4b demonstrates that these new patents are more likely to be granted in the US, Europe, or Japan, which is a widely-used indicator of high-quality patents in the literature. In Figure 4c, I further show that the average quality of the patent portfolio increases for domestic firms located in the treated provinces compared to those in other provinces.

3.4 Patent Holders from Home and Abroad Increase Markups

After establishing that enhanced patent protection facilitates access to advanced technologies, this subsection documents how stronger patent protection affects the markups of patent holders and discusses how the empirical findings motivate the quantitative model.

Theoretically, imitators that infringe on others' patents often produce similar products to compete with the patent holders. Consequently, the exit of imitators due to enhanced patent enforcement reduces competition, enabling patent holders to increase their markups. To empirically test this hypothesis, I run the following specification:

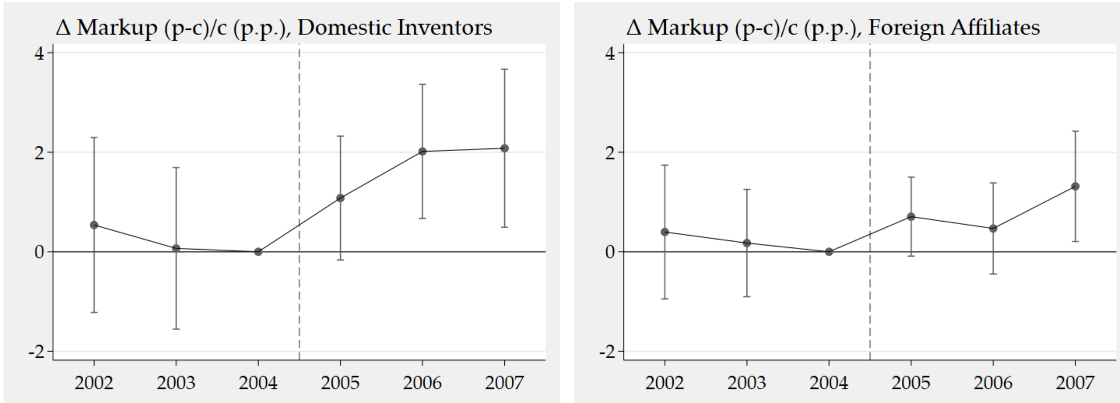
$$\begin{aligned}\ln \mu_{ft} = &\sum_{\tau \neq 2004} \beta_\tau^D \cdot \mathbb{I}\left[l(f) \text{ is treated}\right] \cdot \mathbb{I}\left[t=\tau\right] \cdot \mathbb{I}\left[f \text{ is a domestic patent holder}\right] \\ &+ \sum_{\tau \neq 2004} \beta_\tau^F \cdot \mathbb{I}\left[l(f) \text{ is treated}\right] \cdot \mathbb{I}\left[t=\tau\right] \cdot \mathbb{I}\left[f \text{ is a foreign affiliate}\right] \\ &+ FE_{l(f)j(f)t} + FE_f + FE_{c(f)t} + \varepsilon_{ft}, \end{aligned} \tag{3}$$

where μ_{ft} represents the firm-level markup charged by firm f in year t. $\vec{\beta}^D$ and $\vec{\beta}^F$ capture the year-by-year impacts of locating in a treated province for domestic patent holders and foreign affiliates, respectively, relative to the control group of domestic firms that never patent.

Identification of the causal impacts hinges crucially on the categories of firms and the incorporation of fixed effects. By controlling for province-industry-year fixed effects, $FE_{l(f)j(f)t}$, the analysis focuses on within-province-industry variations in markup changes across different firm categories. This approach parallels the underlying assumption depicted in Figure 2. Given that enhanced patent protection primarily benefits firms holding patents, domestic firms without patents are not expected to experience direct effects on their markups; their markup changes would mostly reflect equilibrium impacts. Consequently, the markup responses of patent holders (i.e., domestic inventors and foreign affiliates) relative to the control group within the same province-industry would reflect the causal impacts stemming from enhanced patent enforcement.

In addition, I include firm-level and category-year fixed effects to account for potential confounding factors. Firm-level fixed effects, FE_f control for time-invariant characteristics such as a firm's fundamental labor productivity. Category-year fixed effects, $FE_{c(f)t}$, control for factors such as national policies that target foreign affiliates or patent holders, ensuring that category-specific shocks are not misattributed to the IPR intervention.

Since the data lacks direct measures of prices and marginal costs, measuring markups directly is not feasible. Instead, I adopt a structural approach proposed by De Loecker and Warzynski (2012), following the methodology outlined in Brooks, Kaboski and Li (2021). The fundamental concept is to impose the first-order condition for a flexibly chosen factor (in this case intermediate inputs) and express the markup μ_{ft} as the ratio of the factor's output elasticity to its expenditure shares in revenue. While expenditure shares on intermediate inputs are



(a) Domestic Patent Holders ($\vec{\beta}^D$)

(b) Foreign Firms ($\vec{\beta}^F$)

Figure 5: Markup Responses of Patent Holders

Notes: This figure examines how enhanced patent enforcement affects markups of domestic patent holders and foreign affiliates. The plots present the regression coefficients in (3) for two different firm categories. Fixed effects are controlled for at the firm level, category-year level and the province-industry-year level, with standard errors clustered at the province-year level. Industries are at the level of 2-digit International Standard Industrial Classification (ISIC Rev. 4). Regression details are reported in Table A.4.

observable, estimating the output elasticity necessitates modeling the production function. I employ the method introduced by Ackerberg, Caves and Frazer (2015) to estimate the output elasticity, utilizing a third-order translog production function. Further details are provided in Appendix A.3.[8]

Figure 5 reports the regression results. The results indicate that compared to the controlled group within the same province-industry, both domestic patent holders and foreign firms in the treated provinces raise their markups following the enhancement of patent protection. On average, domestic patent holders increase their markups by 2 p.p., while foreign firms show a 1 p.p. increase, with both changes being statistically significant.

The empirical findings show that enhanced patent protection leads to simultaneous increases in technology adoption and markups for both multinationals and domestic inventors, with the rise in technology adoption mainly driven by cutting-edge technologies. This pattern highlights a trade-off from a social welfare perspective, balancing the benefits of access to high-quality technologies against the costs of increased market power. To quantitatively assess the aggregate impact of patent protection, a framework is needed to disentangle these within-firm mechanisms and provide structure for aggregation across firms and industries.

[8] A common concern of using Chinese firm-level data to estimate markups is the absence of quantity information. To address this, I follow Brandt, Van Biesebroeck, Wang and Zhang (2017) and apply price deflators to both revenue for output and fixed assets for capital inputs. Still, using revenue to estimate the production function can introduce bias in the output elasticity due to price-elasticity of demand. As De Ridder, Grassi and Morzenti (2024) recently highlight, however, while the absolute levels of markups may be biased, trends in markups and their dispersion across firms are still reliably measured. Since my analysis focuses on within-firm changes over time and across-firm variations within province-industry groups, the potential bias from lacking quantity data is unlikely to affect the core results.

4 Model

In this section, I present a model with microfoundations linking patent infringement activities to firms' endogenous decisions on markups and technology adoption. The model provides a framework to aggregate within-firm mechanisms into the overall impacts of patent protection, while incorporating rich firm heterogeneity to facilitate subsequent quantitative analysis.

4.1 Environment

Consider an economy with two countries, Home and Foreign. I concentrate on the Home market. Foreign firms should establish production affiliates in Home to sell in this market. There are $J+1$ industries, where $j=0$ represents an industry with homogeneous goods taken as the numeraire, and $j=1,...,J$ denote industries with heterogeneous products that feature endogenous entry and imitation. Home is endowed with L units of labor, which is the only factor of production.

Timeline. The model is static, but decisions are made sequentially. In each differentiated industry $j \geq 1$, the economy is endowed with a continuum of inventors, with measure N_j from Home and N_j^* from Foreign. Each inventor f is endowed with a continuum of *products* $i \in [0,1]$, with product quality $\{\phi_{fi}\}$ independently drawn from an exogenous distribution with c.d.f. $G_{\phi,j}(\cdot)$ for domestic firms or $G^*_{\phi,j}(\cdot)$ for foreign affiliates. Inventors are heterogeneous in both labor productivity and invention efficiency, characterized by (z_f, α_f). Labor productivity z_f is drawn independently from the distributions with c.d.f. $G_{z,j}(\cdot)$ or $G^*_{z,j}(\cdot)$. α_f reflects the cost of invention, drawn independently from distributions with c.d.f. $G_{\alpha,j}(\cdot)$ or $G^*_{\alpha,j}(\cdot)$.

Each inventor f decides whether to develop each product i in its portfolio. For domestic firms, this represents genuine innovation, while for foreign affiliates, this represents technology adoption from its headquarters. Innovation or adoption is costly, with a fixed labor cost $\alpha_f \cdot \phi_i$, which increases with product quality. Upon invention, the firm holds a patent for the product.

Once all inventors have made their decisions on product invention, domestic imitators freely enter the market. An imitator m can select any patented product ω and infringes on the patent, incurring a fixed labor cost F_j^M. The imitator then draws its labor productivity z_m from the distribution $G_{z,j}(\cdot)$ and produces a distinct *variety* of product ω that maintains the same product quality ϕ_ω.

Due to the enforcement of patent protection, an imitator is caught by the government with a probability of $(1-\delta^{-1})$, where $\delta \geq 1$ denotes the strength of patent enforcement. If caught, the imitator is forced to exit before production. All firms, both inventors and imitators, then simultaneously decide on their pricing strategies, followed by production and sales. Lastly, profits from domestic firms are reallocated to consumers, while profits from foreign firms are transferred abroad.

In the remainder of this section, I will solve the model step by step. After introducing the demand structure, I begin with the production decisions, assuming entry is given. Next, I discuss patent enforcement, which determines the entry of imitators, followed by the product invention decisions of inventors. The section concludes with the derivation of the aggregation and the definition of the equilibrium.

Demand. Consumers derive utility using a Cobb-Douglas aggregator over all industries:

$$U = \prod_{j=0}^{J} X_j^{\beta_j}, \text{ where } \sum_{j=0}^{J} \beta_j = 1. \tag{4}$$

Within each industry $j \geq 1$, there is a continuum of *products* indexed by $\omega \in \Omega_j$,

$$X_j = \left[\int_{\Omega_j} \phi(\omega)^{\frac{1}{\sigma}} \cdot x(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega \right]^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where $\sigma > 1$ is the elasticity of substitution, and Ω_j is the set of j products available in the market. Products vary in quality, as indicated by $\phi(\omega)$.

Each product ω comprises differentiated *varieties*:

$$x(\omega) = \left[x^I(\omega)^{\frac{\eta-1}{\eta}} + \int_0^{M(\omega)} x^m(\omega)^{\frac{\eta-1}{\eta}} \mathrm{d}m \right]^{\frac{\eta}{\eta-1}}, \tag{6}$$

where $\eta > \sigma$ is the elasticity of substitution among varieties within each product. Each product ω involves two types of firms: the *inventor* (firm I) and *imitators* (firms m), the latter forming a total mass $M(\nu)$ and each producing a distinct variety. Consumers apply the same elasticity of substitution, η, to varieties from both the inventor and the imitators.

The solution to the utility-maximization problem gives the demand functions

$$x^I(\omega) = \phi(\omega) \cdot \left(\frac{p^I(\omega)}{p(\omega)} \right)^{-\eta} \left(\frac{p(\omega)}{P_j} \right)^{-\sigma} X_j, \tag{7}$$

$$x^m(\omega) = \phi(\omega) \cdot \left(\frac{p^m(\omega)}{p(\omega)} \right)^{-\eta} \left(\frac{p(\omega)}{P_j} \right)^{-\sigma} X_j, \tag{8}$$

where the industry-level and product-level price indexes are

$$P_j = \left[\int_{\Omega_j} \phi(\omega) \cdot p(\omega)^{1-\sigma} \mathrm{d}\omega \right]^{\frac{1}{1-\sigma}}, \tag{9}$$

$$p(\omega) = \left[p^I(\omega)^{1-\eta} + \int_0^{M(\omega)} p^m(\omega)^{1-\eta} \mathrm{d}m \right]^{\frac{1}{1-\eta}}. \tag{10}$$

In the analysis that follows, consider a product ω with quality ϕ in industry j, invented by an inventor f with labor productivity z_f and invention cost α_f. All products sharing the same quality and inventor characteristics behave symmetrically. To simplify tracking, I index a product by (ϕ, z_f, α_f).

4.2 Production and Pricing Decisions

I begin by characterizing the pricing decisions, taking product entry as given. Since α_f, the invention cost, affects only product entry, I omit it in the notation for simplicity until necessary.

Technology and Market Structure. Production uses labor as the sole factor, with the production function given by $y(l) = z \cdot l$, where z is the firm-specific labor productivity. The homogeneous good $j = 0$ is produced with labor productivity W, which pins down the wage rate. In the differentiated industries, product quality ϕ is modeled as a demand shifter and does not affect the production function.

Within each industry $j \geq 1$, there is a continuum of products with varying quality, each developed by an inventor who holds the patent. For product (ϕ, z_f), besides its inventor, a continuum of domestic imitators $[0, M_j(\phi, z_f)]$ produces distinct varieties of this product, where $M_j(\phi, z_f) \geq 0$ denotes the measure of this fringe.[9] Within each product (ϕ, z_f), the market structure is characterized by the competition between the single inventor and the fringe of imitators. Each imitator, being infinitesimal, operates under monopolistic competition, competing only with other varieties within the same product market. In contrast, the inventor engages in oligopolistic competition against the collective fringe of imitators infringing on its patent, internalizing its affect on this product's price index, thereby also competes with other products in the same industry.

Optimal Pricing for Imitators. Imitators vary in labor productivity. For an imitator with labor productivity z_m, it faces the variable profits given by

$$\pi_j^m(\phi, z_f, z_m) = \left[p_j^m(\phi, z_f, z_m) - \frac{W}{z_m} \right] \cdot x_j^m(\phi, z_f, z_m), \tag{11}$$

with $x_j^m(\phi, z_f, z_m)$ subject to the demand (8). Since imitators are infinitesimal and face an elasticity of substitution η, they optimally charge the monopoly markup and set the price as

$$p_j^m(\phi, z_f, z_m) = \mu_\eta \cdot \frac{W}{z_m}, \quad \text{where } \mu_\eta \equiv \frac{\eta}{\eta - 1}. \tag{12}$$

Hence, the price index of the collective imitation fringe can be written as

$$p_j^M(\phi, z_f) = \left[\int_0^{M_j(\phi, z_f)} p_j^m(\phi, z_f, z_m)^{1-\eta} \mathrm{d}m \right]^{\frac{1}{1-\eta}} = \left[M_j(\phi, z_f) \cdot \mu_\eta^{1-\eta} \cdot W^{1-\eta} \cdot \tilde{z}_j^{\eta-1} \right]^{\frac{1}{1-\eta}}, \tag{13}$$

where $\tilde{z}_j$ is the adjusted mean labor productivity defined as

$$\tilde{z}_j \equiv \left[\int_0^{+\infty} z_m^{\eta-1} \mathrm{d}G_{z,j}(z_m) \right]^{\frac{1}{\eta-1}}. \tag{14}$$

Although the model allows for firm heterogeneity among imitators, it remains tractable because the price index of the collective fringe, $p_j^M(\phi, z_f)$, varies across products only with the

[9] The notation is slightly abused here. When $M_j(\phi, z_f) = 0$, the set of imitators is empty.

extensive margin $M_j(\phi, z_f)$ of imitation activities.

Optimal Pricing for an Inventor. The inventor f engages in oligopolistic competition with the collective fringe of imitators, recognizing that the price it charges can affect the product-level price index $p_j(\phi, z_f)$. Taking as given the industry-level aggregates, the inventor chooses its markup to maximize its variable profits

$$\pi_j^I(\phi, z_f) = \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \cdot x_j^I(\phi, z_f), \tag{15}$$

subject to the demand (7). Letting $\varepsilon_j^I(\phi, z_f)$ denote the perceived elasticity of demand faced by the inventor, optimal pricing requires that

$$p_j^I(\phi, z_f) = \mu_j^I(\phi, z_f) \cdot \frac{W}{z_f}, \quad \text{with } \mu_j^I(\phi, z_f) = \frac{\varepsilon_j^I(\phi, z_f)}{\varepsilon_j^I(\phi, z_f) - 1}. \tag{16}$$

Following Atkeson and Burstein (2008), the perceived elasticity of demand is given by[10]

$$\varepsilon_j^I(\phi, z_f) = s_j^I(\phi, z_f) \cdot \sigma + \left[1 - s_j^I(\phi, z_f)\right] \cdot \eta, \tag{17}$$

which is a function of the inventor's *within-product* market share

$$s_j^I(\phi, z_f) = \frac{p_j^I(\phi, z_f)^{1-\eta}}{p_j(\phi, z_f)^{1-\eta}} = \frac{p_j^I(\phi, z_f)^{1-\eta}}{p_j^I(\phi, z_f)^{1-\eta} + p_j^M(\phi, z_f)^{1-\eta}}. \tag{18}$$

Equations (16) to (18) determine the inventor's optimal markup, $\mu_j^I(\phi, z_f)$, as a function of parameters and $p_j^M(\phi, z_f)$, which, by (13), depends solely on $M_j(\phi, z_f)$, the extensive margin of the imitation fringe. As M expands from 0 to $+\infty$, competition within the product market intensifies due to imitators capturing a larger market share, thus reducing s^I from 1 to 0. Consequently, this increased competition drives down the inventor's optimal markup μ^I from $\sigma/(\sigma - 1)$ to $\eta/(\eta - 1)$.

Remark. The market structure I employ has several advantages. First, as in Atkeson and Burstein (2008), the nested CES structure with a discrete inner nest introduces variable markups as a function of market shares. Second, modeling imitators as a continuum allows me to focus on the entry and exit of imitators—the margin affected by patent policy—while simplifying the analysis by enhancing tractability and preventing multiple equilibria, a common challenge in this nested setup with extensive-margin adjustments. This structure is also consistent with the empirical findings in Section 2.1, which show that patent holders are typically few in number but hold substantial market share.[11]

[10] See Appendix B.1 for derivations. Whether the inventor competes with imitators in price or in quantity is not crucial. If the inventor competes in quantity, we would have $\varepsilon_j^I(\phi, z_f) = (s_j^I(\phi, z_f) \cdot \sigma^{-1} + [1 - s_j^I(\phi, z_f)] \cdot \eta^{-1})^{-1}$.

[11] The interaction between a few dominant firms and a fringe of smaller firms was first formalized by Shimomura and Thisse (2012). This paper is the first to apply this framework within the Atkeson and Burstein (2008) model. Additionally, in discussing a verbal IPR model's structure, Maskus (2000, page 112) suggests: "In theoretical terms, therefore, a static model with a dominant foreign firm facing a local competitive fringe makes sense."

4.3 Patent Enforcement and the Entry of Imitators

Imitators freely enter the market. They first incur a fixed imitation cost to infringe a patent, before learning their own labor productivity. With probability $1 - \delta^{-1}$, an imitator gets caught by the government and is forced to exit, where $\delta \geq 1$ reflects the strength of patent enforcement. When $\delta = 1$, there is no patent protection, as the probability of getting caught is zero; when $\delta \to +\infty$, the enforcement is perfect, and the probability of getting caught is one.

Patent enforcement generates profit uncertainty for imitators upon entry. Specifically, the expected profits for an imitator before entry are given by

$$\Pi_j^m(\phi, z_f) \equiv \delta^{-1} \cdot \int_0^{+\infty} \pi_j^m(\phi, z_f, z_m) \mathrm{d}G_{z,j}(z_m) - WF_j^M, \tag{19}$$

where $\pi_j^m(\phi, z_f, z_m)$ denotes the variable profit conditional on a labor productivity z_m, and WF_j^M is the fixed cost of imitation.

For each product (ϕ, z_f), imitators enter the market whenever the expected profits (19) are greater than zero. In equilibrium, either the product is not imitated because (19) is negative, or (19) is driven to zero as imitators crowd in. The equilibrium outcome is characterized by the following proposition.

Proposition 1 (Heterogeneous Imitation)**.** *For a product (ϕ, z_f) in industry j, its product-level price index is given by*

$$p_j(\phi, z_f) = \frac{\sigma}{\sigma - 1} \cdot \frac{W}{z_f} \cdot \min\left\{1, \quad \left[\frac{\hat{\phi}_j(z_f)}{\phi}\right]^{\frac{1}{\eta-\sigma}}\right\}, \tag{20}$$

where $\hat{\phi}_j(z_f)$ is an inventor-specific quality cutoff for imitation:

$$\hat{\phi}_j(z_f) \equiv \delta \cdot z_f^{\eta-\sigma} \cdot \chi_j, \tag{21}$$

with $\chi_j \equiv \frac{WF_j^M}{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot \tilde{z}_j^{\eta-1}}$ and $\tilde{\eta} \equiv (\eta - 1)^{\eta-1}/\eta^\eta$.

Proof. See Appendix B.2. □

Proposition 1 highlights the heterogeneous levels of competition from imitation faced by products with different quality. For a given level of patent enforcement δ, imitators self-select into products with higher quality and less competitive inventors. Within products invented by the same inventor f, there exists a quality cutoff $\hat{\phi}_j(z_f)$ such that only products with quality exceeding the cutoff are imitated; imitating low-quality products is not profitable due to fixed imitation costs. Products not imitated are produced only by the inventor, who charges a monopolistic markup $\sigma/(\sigma - 1)$. Products with higher quality attracts more imitators, which is characterized by a lower $p_j(\phi, z_f)$.

Besides depending on the level of patent enforcement δ, the imitation cutoff $\hat{\phi}_j(z_f)$ increases in the inventor's own labor productivity z_f, indicating that more competitive inventors are relatively less threatened by imitation activities. Also, it is affected by an industry-specific component χ_j, which captures the overall profitability of imitation that hinges upon the aggregate equilibrium outcomes.

When patent enforcement is enhanced, imitators exit the market, which allows inventors to charge a higher markup. Taking the aggregates in the industry as given, this results in an inflation of product-level price indexes. I characterize this impact as a corollary:

Corollary 1 (Patent Enforcement Increases Markups)**.** *Suppose a product (ϕ, z_f) in industry j is imitated, i.e. $M_j(\phi, z_f) > 0$. Following an improvement of patent enforcement that increases δ,*

1. *The inventor f charges a higher markup for this product, namely $\mu_j^I(\phi, z_f)$ increases;*
2. *The product-level price index $p_j(\phi, z_f)$ increases.*

Notably, for low-quality products that are not imitated, an improvement of patent enforcement has no *direct* impact on the pricing decisions of the inventor, who remains the monopoly of this product and engages in monopolistic competition with other products in the industry. Enhanced patent enforcement increases the imitation cutoff $\hat{\phi}_j(z_f)$, leading to more products falling below this threshold and thus not being imitated. In the limit where $\delta \to +\infty$, no imitators enter the market, and the industry is characterized by inventors monopolistically competing with each other.

4.4 Product Invention

Next, I characterize the entry decision for each product. Inventors are heterogeneous in labor productivity and invention cost, represented by (z_f, α_f). Each inventor f is endowed with a unit continuum of products, each having its quality ϕ drawn from a distribution $G_{\phi,j}(\cdot)$ for domestic firms, or $G^*_{\phi,j}(\cdot)$ for foreign affiliates. The inventor decides independently whether to invent each product. For domestic firms, this represents genuine innovation, while for foreign affiliates, this represents technology adoption from its headquarters.

The total profits from inventing a product with quality ϕ are given by

$$\Pi_j^I(\phi, z_f, \alpha_f) = \pi_j^I(\phi, z_f) - W \cdot \alpha_f \cdot \phi, \tag{22}$$

where $\pi_j^I(\phi, z_f)$ represents the variable profit, and the fixed invention cost increases in product quality ϕ, with a rate determined by the invention (in)efficiency α_f.

Depending on the intensity of imitation a product faces, the variable profit of inventing a product varies across product quality and the inventor's labor productivity. The following lemma characterizes the outcome.

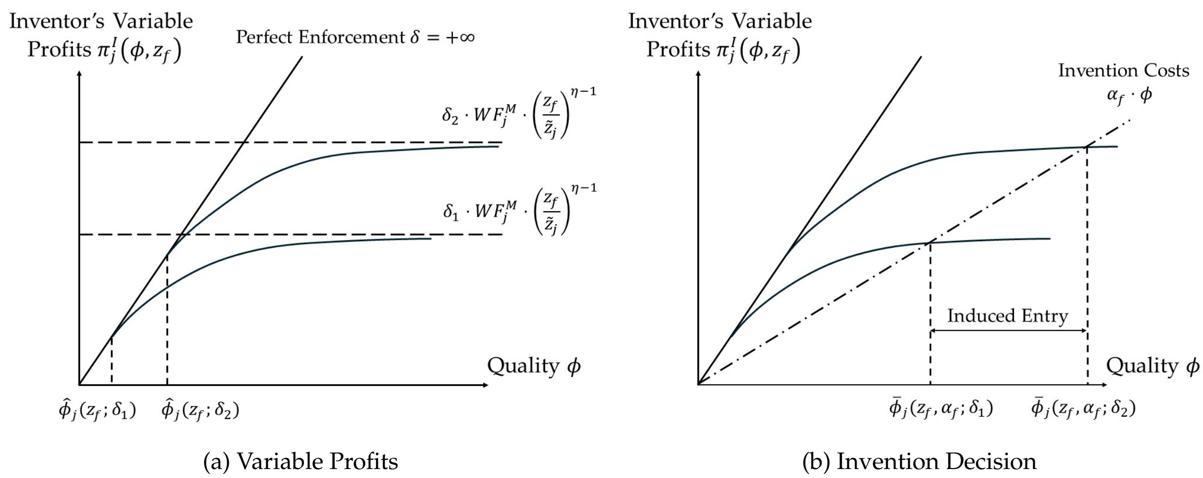


Figure 6: Patent Enforcement and Product Invention

Notes: These figures illustrate how patent enforcement affects an inventor's variable profits and its decision on product invention, conditional on labor productivity z_f and other equilibrium outcomes. Patent enforcement $\delta_1 < \delta_2 < +\infty$.

Lemma 1 (Inventor's Variable Profits). *For a product (ϕ, z_f) in industry j,*

$$\pi_j^I(\phi, z_f) = \begin{cases} \tilde{\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot z_f^{\sigma-1} \cdot \phi & \text{if } \phi \leq \hat{\phi}_j(z_f) \\ \delta \cdot WF_j^M \cdot \left(\dfrac{z_f}{\tilde{z}_j}\right)^{\eta-1} \cdot \kappa_j(\phi, z_f) & \text{if } \phi > \hat{\phi}_j(z_f) \end{cases}, \tag{23}$$

with $\tilde{\sigma} \equiv (\sigma-1)^{\sigma-1}/\sigma^{\sigma}$, and [12]

$$\kappa_j(\phi, z_f) \equiv \tilde{\eta}^{-1} \cdot \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta} \in [\kappa_{\min}, 1)\,. \tag{24}$$

Moreover, for a given z_f, $\kappa_j(\phi, z_f)$ is increasing and concave in $\phi \in (\hat{\phi}_j(z_f), +\infty)$, and asymptotically approaches 1 as $\phi \to +\infty$.

Proof. See Appendix B.3. □

Figure 6a provides a graphical illustration for Lemma 1. With imperfect patent protection, the inventor's variable profit continuously increases with product quality ϕ, but this profit is subject to an upper limit that depends on the level of patent enforcement δ. Intuitively, while higher-quality products secure larger market shares, they also attract more imitation. Consequently, imitators disproportionately capture a greater portion of the market within the product. Enhanced patent enforcement raises this upper limit by allowing inventors to claim a larger market share and charge a higher markup.

[12] $\kappa_{\min} \equiv \frac{(\sigma-1)^{\eta-1}/\sigma^{\eta}}{(\eta-1)^{\eta-1}/\eta^{\eta}} < 1$.

A product (ϕ, z_f, α_f) is invented when the total profits in (22) are positive. This decision can be decomposed into two parts: one based on the firm's labor productivity z_f relative to its invention cost α_f, and the other based on the product's quality ϕ. I characterize the outcomes in the following proposition.

Proposition 2 (Product Invention)**.** *A product (ϕ, z_f, α_f) in industry j is invented if and only if the inventor's labor productivity z_f is not too low and the product quality ϕ is not too high, i.e.,*

$$e_j(\phi, z_f, \alpha_f) = \mathbb{I}\left[z_f > \underline{z}_j(\alpha_f)\right] \cdot \mathbb{I}\left[\phi \leq \bar{\phi}_j(z_f, \alpha_f)\right] \tag{25}$$

1. *The lower cutoff for inventor's labor productivity is given by*

$$\underline{z}_j(\alpha_f) \equiv \left[\frac{W \cdot \alpha_f}{\tilde{\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j}\right]^{\frac{1}{\sigma-1}}, \tag{26}$$

with $\tilde{\sigma} \equiv (\sigma - 1)^{\sigma-1}/\sigma^{\sigma}$.

2. *The upper cutoff for product quality is implicitly determined by*

$$\bar{\phi}_j(z_f, \alpha_f) = \left(\frac{z_f}{\underline{z}_j(\alpha_f)}\right)^{\sigma-1} \cdot \frac{\kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right)}{\kappa_{\min}} \cdot \hat{\phi}_j(z_f), \tag{27}$$

where $\hat{\phi}_j(z_f)$ is the imitation cutoff in (21), and $\kappa_j\left(\phi, z_f\right)$ is defined in (24).

Proof. See Appendix B.4. □

The first part of Proposition 2 states that there exists a firm-level entry condition, such that all firms with $z_f \leq \underline{z}_j(\alpha_f)$ will choose to exit the market without inventing any products. These firms have either relatively low labor productivity or relatively high invention costs. This firm-level entry cutoff depends on the industry-level outcomes determined in equilibrium, illustrating the standard competition effect as in Melitz (2003). The model, in fact, nests Melitz (2003) as a special case when patent enforcement is perfect ($\delta \to +\infty$) and invention costs are homogeneous (i.e., when the distribution of α is degenerate).

The second part of Proposition 2 introduces a new selection mechanism. With imperfect patent enforcement, even if an inventor is capable to enter the market ($z_f > \underline{z}_j(\alpha_f)$), they only introduce a subset of low-quality products with $\phi \leq \bar{\phi}_j(z_f, \alpha_f)$. Top-quality products self-select out of the market due to intense competition from potential imitators. Although higher-quality products capture a larger market share, the inventor can only secure a small portion of it, which is insufficient to cover the initial invention costs. Figure 6b provides a graphical illustration of this mechanism. Notably, this upper cutoff for product quality $\bar{\phi}_j(z_f, \alpha_f)$ increases as δ increases—when patent enforcement is enhanced, inventors are able to reclaim a larger market share, which disproportionately induces top-quality products to enter the market. I summarize this impact as a second corollary:

Corollary 2 (Patent Enforcement Induces Top-Quality Inventions)**.** *Following an improvement of patent enforcement that increases δ, for all inventors f, the upper entry cutoff for product quality, $\bar{\phi}_j(z_f, \alpha_f)$, increases.*

4.5 Aggregation and Equilibrium

The analysis thus far has focused on the individual product level. To close the model, I will now derive the aggregate variables. The formal definition and characterization of the equilibrium is provided in Appendix B.5.

At a firm level, the price index for all products invented by an inventor (z_f, α_f) can be written as

$$P_j(z_f, \alpha_f)^{1-\sigma} = \int_0^{+\infty} e_j(\phi, z_f, \alpha_f) \cdot \phi \cdot p_j(\phi, z_f)^{1-\sigma} \, \mathrm{d}G_{\phi,j}(\phi), \tag{28}$$

$$P_j^*(z_f, \alpha_f)^{1-\sigma} = \int_0^{+\infty} e_j(\phi, z_f, \alpha_f) \cdot \phi \cdot p_j(\phi, z_f)^{1-\sigma} \, \mathrm{d}G^*_{\phi,j}(\phi), \tag{29}$$

where $p_j(\phi, z_f)$ is given by (20), $e_j(\phi, z_f, \alpha_f)$ is given by (25), and $G_{\phi,j}(\phi)$ and $G^*_{\phi,j}(\phi)$ are the product quality distributions for Home and Foreign, respectively.

Aggregating over all firms in an industry, the industry-level price index is then

$$P_j^{1-\sigma} = N_j \int\int P_j(z_f, \alpha_f)^{1-\sigma} \mathrm{d}G_{z,j}(z_f) \mathrm{d}G_{\alpha,j}(\alpha_f) + N_j^* \int\int P_j^*(z_f, \alpha_f)^{1-\sigma} \mathrm{d}G^*_{z,j}(z_f) \mathrm{d}G^*_{\alpha,j}(\alpha_f). \tag{30}$$

With $P_0 \equiv 1$, the ideal aggregate price index is

$$P = \prod_{j=0}^{J} \left(P_j / \beta_j\right)^{\beta_j}. \tag{31}$$

Aggregate income comes from wages and profits of domestic firms, given by

$$E = WL + \sum_{j=1}^{J} N_j \int\int \Pi_j(z_f, \alpha_f) \mathrm{d}G_{z,j}(z_f) \mathrm{d}G_{\alpha,j}(\alpha_f), \tag{32}$$

where firm-level profits are

$$\Pi_j(z_f, \alpha_f) = \int_0^{+\infty} e_j(\phi, z_f, \alpha_f) \cdot \Pi_j^I(\phi, z_f, \alpha_f) \, \mathrm{d}G_{\phi,j}(\phi), \tag{33}$$

with $\Pi_j^I(\phi, z_f, \alpha_f)$ given by (22). Finally, by (4), the aggregate income is spent proportionally to different industries, i.e.,

$$P_j X_j = \beta_j E, \ \forall j. \tag{34}$$

4.6 The Aggregate Impacts of Patent Protection

Before taking the model to data, it is useful to develop more intuition about how patent protection affects the equilibrium. In this subsection, I characterize the direct impacts of patent enforcement δ on real income E/P. These direct impacts closely align with the mechanisms highlighted by the reduced-form evidence in Section 3, namely, the increase in inventors' market power and access to higher quality technologies.

To see how aggregate income E changes when patent enforcement δ changes, note that

$$\begin{aligned}\frac{\mathrm{d}E}{\mathrm{d}\delta} = \sum_{j=1}^{J} N_j \Bigg(\int_0^{+\infty} \int_{\underline{z}_j(\alpha_f)}^{+\infty} \Bigg[& \underbrace{\int_0^{\hat{\phi}_j(z_f)} \frac{\partial \pi_j^I(\phi, z_f)}{\partial \delta} \mathrm{d}G_{\phi,j}(\phi)}_{\text{Eqm. (Product Int. Margin)}} + \underbrace{\int_{\hat{\phi}_j(z_f)}^{\bar{\phi}_j(z_f,\alpha_f)} \frac{\partial \pi_j^I(\phi, z_f)}{\partial \delta} \mathrm{d}G_{\phi,j}(\phi)}_{(+)\text{ Market Power}} \\ & + \underbrace{\frac{\partial \bar{\phi}_j(z_f, \alpha_f)}{\partial \delta} \Pi_j^I\left(\bar{\phi}_j(z_f), z_f, \alpha_f\right) g_{\phi,j}\left(\bar{\phi}_j(z_f,\alpha_f)\right)}_{(+)\text{ Entry of Top Products}} \Bigg] \mathrm{d}G_{z,j}(z_f)\mathrm{d}G_{\alpha,j}(\alpha_f) \\ & + \underbrace{\int_0^{+\infty} -\frac{\mathrm{d}\underline{z}_j(\alpha_f)}{\mathrm{d}\delta} \cdot \Pi_j\left(\underline{z}_j(\alpha_f), \alpha_f\right) \cdot g_{z,j}\left(\underline{z}_j(\alpha_f)\right) \mathrm{d}G_{\alpha,j}(\alpha_f)}_{\text{Eqm. (Firm Ext. Margin)}} \Bigg) \end{aligned} \tag{35}$$

In this partial equilibrium setting, patent protection affects aggregate income by changing the aggregate profits of domestic inventors. These changes, as shown in equation (35), can be decomposed into three parts. First, for incumbent products that are imitated, domestic inventors secure a larger market share from imitators, allowing them to earn higher profits through increased markups. Second, stronger patent protection enables domestic inventors to introduce top-quality products that previously self-selected out of the market under weaker protection, generating positive profit flows. Lastly, domestic profits are shaped by the overall level of competition, such as the entry and exit of foreign products, captured by the equilibrium changes in price indexes P_j, which influence aggregate profits via the profitability of incumbent products (intensive margin) and the entry/exit of domestic firms (extensive margin).

Apart from affecting aggregate income, patent protection shapes real income by altering aggregate price indexes P_j. Equation (36) below provides a similar decomposition for these effects. While the increase in market power generates profits for inventors, it reduces consumer welfare through price inflation, which becomes the primary source of welfare loss.

$$
\begin{aligned}
\frac{\mathrm{d}P_j^{1-\sigma}}{\mathrm{d}\delta} = N_j \int_0^{+\infty} \int_{\underline{z}_j(\alpha_f)}^{+\infty} \Bigg[& \underbrace{\int_{\hat{\phi}_j(z_f)}^{\bar{\phi}_j(z_f,\alpha_f)} \left(\frac{\sigma}{\sigma-1}\frac{W}{z_f}\right)^{1-\sigma} \frac{\partial}{\partial\delta}\left(\frac{\hat{\phi}_j(z_f)}{\phi}\right)^{\frac{1-\sigma}{\eta-\sigma}} \mathrm{d}G_{\phi,j}(\phi)}_{(-)\text{ Home Market Power}} \\
& + \underbrace{\frac{\partial\bar{\phi}_j(z_f,\alpha_f)}{\partial\delta} p_j\left(\bar{\phi}_j(z_f,\alpha_f), z_f\right)^{1-\sigma} g_{\phi,j}\left(\bar{\phi}_j(z_f,\alpha_f)\right)}_{(+)\text{ Entry of Top Home Products}} \Bigg] \mathrm{d}G_{z,j}(z_f)\mathrm{d}G_{\alpha,j}(\alpha_f) \\
+ N_j^* \int_0^{+\infty} \int_{\underline{z}_j(\alpha_f)}^{+\infty} \Bigg[& \underbrace{\int_{\hat{\phi}_j(z_f)}^{\bar{\phi}_j(z_f,\alpha_f)} \left(\frac{\sigma}{\sigma-1}\frac{W}{z_f}\right)^{1-\sigma} \frac{\partial}{\partial\delta}\left(\frac{\hat{\phi}_j(z_f)}{\phi}\right)^{\frac{1-\sigma}{\eta-\sigma}} \mathrm{d}G^*_{\phi,j}(\phi)}_{(-)\text{ Foreign Market Power}} \\
& + \underbrace{\frac{\partial\bar{\phi}_j(z_f,\alpha_f)}{\partial\delta} p_j^*\left(\bar{\phi}_j(z_f,\alpha_f), z_f\right)^{1-\sigma} g^*_{\phi,j}\left(\bar{\phi}_j(z_f,\alpha_f)\right)}_{(+)\text{ Entry of Top Foreign Products}} \Bigg] \mathrm{d}G^*_{z,j}(z_f)\mathrm{d}G^*_{\alpha,j}(\alpha_f) \\
& \underbrace{\begin{aligned} - N_j \int_0^{+\infty} \frac{\mathrm{d}\underline{z}_j(\alpha_f)}{\mathrm{d}\delta} \cdot P_j\left(\underline{z}_j(\alpha_f), \alpha_f\right)^{1-\sigma} \cdot g_{z,j}\left(\underline{z}_j(\alpha_f)\right) \mathrm{d}G_{\alpha,j}(\alpha_f) \\ - N_j^* \int_0^{+\infty} \frac{\mathrm{d}\underline{z}_j(\alpha_f)}{\mathrm{d}\delta} \cdot P_j^*\left(\underline{z}_j(\alpha_f), \alpha_f\right)^{1-\sigma} \cdot g^*_{z,j}\left(\underline{z}_j(\alpha_f)\right) \mathrm{d}G^*_{\alpha,j}(\alpha_f)\end{aligned}}_{\text{Eqm. (Firm Ext. Margin)}}
\end{aligned}
\tag{36}
$$

The trade-off between market power and access to advanced technologies is most pronounced within the product portfolio of a firm (z_f, α_f). On the one hand, intensified patent enforcement grants inventors more market power by reducing competition from imitators, allowing them to raise markups on their existing products, thereby inflating the price index and harming consumer welfare. This effect depends on the mass of infra-marginal products, as described by the integrated c.d.f.'s $\mathrm{d}G_{\phi,j}(\cdot)$ and $\mathrm{d}G^*_{\phi,j}(\cdot)$. On the other hand, higher-quality products are induced to enter the market, which drives down the aggregate price index. The size of this effect depends on the mass of entering products, characterized by the p.d.f.'s at the cutoffs, i.e., $g_{\phi,j}\left(\bar{\phi}_j(z_f,\alpha_f)\right)$ and $g^*_{\phi,j}\left(\bar{\phi}_j(z_f,\alpha_f)\right)$. At the aggregate level, the overall impact on the industry price index is a weighted average of these trade-offs across all firms, along with the entry and exit of firms at the extensive margin, both of which depend on the distribution of firms' labor productivity z_f and invention costs α_f.

In general, the distributions of ϕ, z_f, and α_f can differ across countries and industries. However, patent enforcement δ applies uniformly across firms in all industries, regardless of the source of technologies. As a result, the optimal level of patent enforcement hinges on the specific technology distributions and the relative industry weights (i.e., β_j) of the economy. In the remainder of the paper, I will calibrate these fundamental elements using Chinese firm-level data to assess the trade-offs between market power and technology access discussed above, thereby quantifying the aggregate gains and losses of patent protection.

5 Calibration

This section introduces the procedures to calibrate the model using Chinese firm-level data. I describe parameterization in Section 5.1, moments and identification in Section 5.2, and presents the calibration results in Section 5.3.

5.1 Parameterization and Additional Structure

I start with introducing the additional functional forms to parameterize the model.

Product Quality Distributions $G_{\phi,j}(\cdot)$ and $G^*_{\phi,j}(\cdot)$. Product quality ϕ follows a Pareto distribution with scale parameter 1 and shape parameter θ_j and θ^*_j for Home and Foreign, respectively. Thus, $G_{\phi,j}(\phi) = 1 - \phi^{-\theta_j}$ for Home and $G^*_{\phi,j}(\phi) = 1 - \phi^{-\theta^*_j}$ for Foreign.

Labor Productivity Distribution $G_{z,j}(\cdot)$ and $G^*_{z,j}(\cdot)$. Labor productivity z_f follows a log-normal distribution with mean and variance parameters $\tau_{z,j}$ and $\nu_{z,j}$ for Home inventors, and $\tau^*_{z,j}$ and $\nu^*_{z,j}$ for Foreign affiliates. Imitators draw their labor productivity from the same distribution as Home inventors.

Innovation/Adoption Cost Distribution $G_{\alpha,j}(\cdot)$ and $G^*_{\alpha,j}(\cdot)$. The invention cost variable α_f is also log-normally distributed, with mean and variance parameters $\tau_{\alpha,j}$ and ν_α for Home inventors introducing new technologies, and $\tau^*_{\alpha,j}$ and ν^*_α for Foreign affiliates adopting technologies from headquarters.

Imitation Costs F^M_j. In the model, patent enforcement δ and the fixed costs of imitation F^M_j cannot be separately identified. To address this, I introduce an additional structure on F^M_j by assuming that $\hat{\phi}_j(\tilde{z}_j)|_{\delta=1} = 1$, meaning all patents are imitated for inventors with $z_f \leq \tilde{z}_j$ when there is no patent enforcement. With this restriction, F^M_j is calibrated jointly with other parameters in each iteration.

5.2 Identification and Calibration Procedures

The fundamentals in the model include parameters on preference $\{\beta_j, \sigma, \eta\}$, wages and labor $\{W, L\}$, measure of inventors $\{N_j, N^*_j\}$, their distributions over labor productivity characterized by $\{\tau_{z,j}, \tau^*_{z,j}, \nu_{z,j}, \nu^*_{z,j}\}$, invention efficiency characterized by $\{\tau_{\alpha,j}, \tau^*_{\alpha,j}, \nu_{\alpha,j}, \nu^*_{\alpha,j}\}$, and product quality characterized by $\{\theta_j, \theta^*_j\}$, the fixed costs of imitation $\{F^M_j\}$ and the patent enforcement level δ. I calibrate these parameters to the Chinese firm-level data, as described in Section 2.1, using the cross-section in 2004 before the IPR campaign. Some parameters are externally calibrated, while the remaining are jointly determined to match a set of moments. In this subsection, I discuss the calibration procedure, the intuition on identification, and the numerical algorithm.

Industries. My analysis focuses on patent-intensive industries, as defined in Section 2.1.[13] For computational simplicity, I further aggregate them into six industries: Metal Products and Machinery (25, 28, 32), Chemicals (20), Pharmaceuticals (21), Transport Equipment (29, 30), Electrical Equipment (27), and Electronics (26), with the numbers in parentheses indicating the corresponding ISIC codes. The industry weights β_j are set to match their sales share in the manufacturing sector, and all other non-patent-intensive industries are treated as the homogeneous numeraire good.

Wages, Labor, and Measure of Firms. I normalize wage $W = 1$, labor supply $L = 1$, and the measure of Home inventors $N_j = 1$ for all industries j. The measure of Foreign inventors N_j^* is calibrated jointly with other parameters to match the aggregate market share of foreign affiliates relative to Chinese inventors in equilibrium.

Elasticities. The elasticity of substitution across products is set to $\sigma = 3.5$, corresponding to a maximum inventor markup of 40%, which aligns with the 75th percentile of patent holders' markups in the data. The elasticity of substitution across varieties within a product is set to $\eta = 9$, resulting in an imitator markup of 12.5%, matching the 25th percentile of markups for Chinese firms without patents.

Product Quality Distributions $G_{\phi,j}(\cdot)$ and $G^*_{\phi,j}(\cdot)$. I match the distributions of product quality ϕ to patent quality distributions introduced in Section 2.1, assuming that $\phi(\omega) = 1 + \varphi(\omega)$, where the patent quality $\varphi(\omega)$ is the patent's forward citations relative to the average in the same year. Since products self-select into the market, the underlying quality distribution differs from the observed distribution of market entrants. To address this, I calibrate θ_j^* to match the quality distribution of all patents invented globally by multinational firms, regardless of whether they are patented in China. The parameter θ_j for Home inventors is calibrated jointly with other model parameters to fit the observed quality distribution of patents filed by Chinese firms.

Distributions of Labor Productivity and Innovation/Adoption Cost. I jointly calibrate the labor productivity distributions, $G_{z,j}(\cdot)$ and $G^*_{z,j}(\cdot)$, and the invention cost distributions, $G_{\alpha,j}(\cdot)$ and $G^*_{\alpha,j}(\cdot)$, using firm-level sales distributions and patent entry distributions for multinational firms.

To see how identification is established with these two sets of moments, consider the top-

[13] See Table A.1 for the full list of industries.

Table 2: Moments for Calibration

Moments	# Moments	Parameters
External		
Industry Shares	6	β_j
Mean of MNE Global Patent Quality	6	θ_j^*
Internal		
Mean of Entered Home Patent Quality	6	θ_j
Market Share of Imitators	6	δ
Relative Market Share of Foreign to Home Inventors	6	N_j^*
Mean and Std. Dev. of Logged Sales (Home)	12	$\tau_{z,j}, \nu_{z,j}$
Mean and Std. Dev. of Logged Sales (Foreign)	12	$\tau_{z,j}^*, \nu_{z,j}^*$
10th, 50th, 90th percentile of Above-Median Patent Entry Rate	36	$\tau_{\alpha,j}, \nu_{\alpha,j}, \tau_{\alpha,j}^*, \nu_{\alpha,j}^*,$

Notes: This table lists the targeted moments used for calibration. The external moments are exactly matched to pin down $\{\beta_j, \theta_j^*\}$, and the internal moments are targeted to jointly calibrate the remaining parameters $\{\delta, \tau_{z,j}, \tau_{z,j}^*, \nu_{z,j}, \tau_{\alpha,j}, \tau_{\alpha,j}^*, \nu_{\alpha,j}, \theta_j, N_j^*\}$. The last column links moments to parameters that they best help identify. Logged sales are demeaned for all industries in both the data and the model.

quality cutoff $\bar{\phi}_j(z_f, \alpha_f)$ and sales $r_j^I(z_f, \alpha_f)$ for an inventor:

$$\ln \bar{\phi}_j(z_f, \alpha_f) = (\eta - 1)\ln z_f - \ln \alpha_f + \ln\left(\delta \cdot WF_j^M \cdot \tilde{z}_j^{1-\eta}\right) + \ln \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right), \tag{37}$$

$$\ln r_j^{I(*)}(z_f, \alpha_f) = (\sigma - 1)\ln z_f + \ln\left[\int_0^{\bar{\phi}_j(z_f,\alpha_f)} \mu_j^I(\phi, z_f)^{1-\eta} \min\left(\phi,\ \hat{\phi}(z_f)\right) \mathrm{d}G_{\phi,j}^{(*)}(\phi)\right] + \ln C_j, \tag{38}$$

where $C_j = \left(\frac{\sigma}{\sigma-1}\right)^{\eta-\sigma} W^{1-\sigma} P_j^\sigma X_j$ is an industry-specific component. Intuitively, while $\ln z_f$ and $\ln \alpha_f$ appear in both equations, variation in sales (38) is primarily driven by $\ln z_f$, whereas the entry cutoff (37) is driven by the difference between $\ln z_f$ and $\ln \alpha_f$. Thus, Foreign parameters rely on the distribution of $\ln r_j^{I*}(z_f, \alpha_f)$ to identify $\{\tau_{z,j}^*, \nu_{z,j}^*\}$, and jointly on the distribution of $\ln \bar{\phi}_j(z_f, \alpha_f)$ for $\{\tau_{\alpha,j}^*, \nu_{\alpha,j}^*\}$.

In practice, directly measuring $\bar{\phi}_j(z_f, \alpha_f)$ with the maximal quality of patented inventions may be too extreme. Instead, it is more reasonable to match the share of inventions that are patented in China, which requires a monotonic transformation from $\bar{\phi}_j(z_f, \alpha_f)$ to $G_{\phi,j}^*\left(\bar{\phi}_j(z_f, \alpha_f)\right)$. Since my model abstracts from patenting costs—which may selectively discourage lower-quality patents from being filed—I use the patenting share of each firm's above-median patents and match this with $\tilde{G}_{\phi,j}^*(z_f, \alpha_f) \equiv \max\left\{2 \times G_{\phi,j}^*\left(\bar{\phi}_j(z_f, \alpha_f)\right) - 1, 0\right\}$.

A key challenge is that the patent entry distribution for Chinese firms is unobserved. Hence, I have to assume that the above-median patent entry rate follows the same distribution between firms from different countries, thereby relying on the distributions of $\ln r_j^I(z_f, \alpha_f)$ and $\tilde{G}_{\phi,j}^*(z_f, \alpha_f)$ to identify Home parameters.

Table 3: Calibrated Model Parameters

Parameter	Notation	Metal & Machinery	Chemicals	Pharmaceuticals	Transport Equipment	Electrical Equipment	Electronics
Industry Share	β_j	0.11	0.09	0.02	0.09	0.06	0.14
Measure of Foreign Firms	N_j^*	6.93	4.15	1.24	4.50	5.12	6.46
Product Quality Dist. (Home)	θ_j	2.65	1.79	6.69	3.15	2.03	2.11
Product Quality Dist. (Foreign)	θ_j^*	2.09	1.71	1.96	2.15	2.08	1.94
Labor Prod. Dist. (mean, Home)	$\tau_{z,j}$	-0.33	-0.54	-0.42	-0.01	-0.31	-0.20
Labor Prod. Dist. (var, Home)	$\nu_{z,j}$	0.42	0.45	0.73	0.40	0.42	0.49
Labor Prod. Dist. (mean, Foreign)	$\tau_{z,j}^*$	-0.08	-0.54	-0.57	-0.71	-0.44	-0.09
Labor Prod. Dist. (var, Foreign)	$\nu_{z,j}^*$	0.18	0.27	0.69	0.55	0.38	0.80
Innovation Cost Dist. (mean, Home)	$\tau_{\alpha,j}$	-7.80	-5.92	-8.87	-5.87	-6.07	-5.44
Innovation Cost Dist. (var, Home)	$\nu_{\alpha,j}$	0.70	0.70	0.70	0.70	0.70	0.70
Adoption Cost Dist. (mean, Foreign)	$\tau_{\alpha,j}^*$	-8.19	-6.25	-9.42	-7.69	-7.36	-8.26
Adoption Cost Dist. (var, Foreign)	$\nu_{\alpha,j}^*$	0.86	0.86	0.86	0.86	0.86	0.86
Imitation Costs ($\times 0.01$)	F_j^M	0.55	2.77	1.69	2.57	1.11	0.45
Patent Enforcement	$\delta = 1.01$						

Notes: This table lists the calibrated parameters. Other parameters include: $W = 1$, $L = 1$, $\sigma = 3.5$, $\eta = 9.0$, and $N_j = 1$ for all j.

Patent Enforcement δ. The patent enforcement level δ is calibrated to match the average market share of imitators, specifically Chinese firms without patents.

Numerical Implementation. I employ a nested algorithm for the calibration. In the outer layer, I search across the parameters in $\{\delta, \tau_{z,j}, \tau_{z,j}^*, \nu_{z,j}, \tau_{\alpha,j}, \tau_{\alpha,j}^*, \nu_{\alpha,j}, \theta_j, N_j^*\}$ to minimize the difference between model moments and their data counterparts. As listed in Table 2, these moments include the aggregate market shares of different category of firms, the mean of observed Chinese patents, the mean and standard deviation of the logged sales distributions for both Home and Foreign inventors (corresponding to Chinese patent holders and foreign affiliates) as well as different percentiles of firm-level above-median quality patent entry rates, $\tilde{G}_{\phi,j}^*(z_f, \alpha_f)$. In the inner layer, I first solve for the equilibrium with $\delta = 1$ (i.e., no protection) while restricting $\hat{\phi}_j(\tilde{z}_j)|_{\delta=1} = 1$ to calibrate F_j^M, and then solve for the equilibrium with the calibrated F_j^M and the δ fed from the outer layers.

5.3 Calibration Results and Model Fit

Table 3 displays the calibrated parameters. As is shown in Table C.1, the model fits the data reasonably well. By observing the calibrated parameters, several patterns emerge. First, the product quality distribution of Foreign firms consistently dominates that of Home across industries, indicating that foreign patents are generally of higher quality than Chinese patents. Second, on average, $\tau_{\alpha,j}$ is larger than $\tau_{\alpha,j}^*$, consistent to the different nature of invention by domestic and foreign firms—one is genuine innovation, while the other is adopting an existing technology or product into Chinese market. Lastly, the calibrated parameter δ suggests that the baseline level of patent enforcement is quite low, with imitators facing only a 1% probability of being caught ($1 - \delta^{-1}$).

6 Quantitative Analysis

To assess the aggregate impacts of patent protection, I use the calibrated model to conduct several counterfactual experiments. In Section 6.1, I evaluate the aggregate effects of the 2004 IPR campaign implemented by the Chinese government, revealing that the enhancement of patent enforcement was welfare-improving overall but exhibited significant industry heterogeneity. In Section 6.2, I decompose these impacts into different mechanisms, highlighting the key trade-off between increased market power and the within-firm selection in technology adoption. Finally, in Section 6.3, I investigate the general optimality of patent protection levels.

6.1 Evaluating the 2004 IPR Campaign in China

How did the 2004 enhancement of patent protection in China affect the aggregate real income? To answer this question, I use the model to conduct a counterfactual analysis that simulates the patent enforcement level in 2004. In the reduced-form analysis in Section 3.2, I document that the improvement in patent enforcement led multinational firms to adopt their leading technologies in China, with a 15% rise in the share of top 10% quality patents. I take this empirical finding as a calibration target for the strength of patent enhancement. Specifically, holding other parameters fixed, I vary the patent enforcement parameter δ until the average entry share of the top 10% quality products of incumbent Foreign firms increases by 15%, which yields the ex-post patent enforcement level. Since my model does not capture geographic variations, this counterfactual experiment should be interpreted as a longer-term, country-wide consequences of patent enforcement reforms, which also aligns with China's broader policy shift towards enhanced patent protection.[14]

Table 4 presents the changes in aggregate variables by comparing the new equilibrium with the status quo. Panel A shows that enhanced patent protection is overall welfare-improving, raising aggregate real income by 0.83%. This increase is driven by a 0.3% rise in nominal income and a 0.54% reduction in the aggregate price index. Although domestic total profits take up only a small share of aggregate nominal income, the enhanced patent protection led to a significant increase in Home inventors' total profits, up by around 25.6%. The gain for Foreign profits is even more substantial, with an increase of approximately 32.72%. This supports the

[14] In fact, in 2008, the Chinese central government designated Intellectual Property Rights as a "key national strategy," emphasizing that 'efforts to strengthen intellectual property work must be diligently pursued."

Table 4: Aggregate Impacts of the 2004 IPR Campaign in China

Panel A. Aggregate Impacts

Description		Changes (% in p.p.)
Real Income,	$\Delta \ln [(WL+\Pi)/P]$	0.83
Nominal Income,	$\Delta \ln (WL+\Pi)$	0.30
Aggregate Price Index,	$\Delta \ln P = \sum_j \beta_j \Delta \ln P_j$	-0.54
Home Total Profits,	$\Delta \ln \Pi = \sum_j (\Pi_j/\Pi) \Delta \ln \Pi_j$	25.60
Foreign Total Profits,	$\Delta \ln \Pi^* = \sum_j (\Pi_j^*/\Pi^*) \Delta \ln \Pi_j^*$	32.72

Panel B. Industry Decomposition

	Metal & Machinery	Chemicals	Pharmaceu-ticals	Transport Equipment	Electrical Equipment	Electronics
Price Index, $\beta_j \Delta \ln P_j$	-0.11	-0.57	0.06	-0.00	-0.14	0.22
Home Profits, $(\Pi_j/\Pi) \Delta \ln \Pi_j$	2.52	6.13	2.27	10.76	3.40	0.28
Foreign Profits, $(\Pi_j^*/\Pi^*) \Delta \ln \Pi_j^*$	5.69	4.78	2.77	4.39	4.28	7.35

Notes: This table presents the aggregate impacts of the 2004 IPR campaign in China with decomposition into different industries. See Appendix C.2 for the derivations of decomposition. All numbers represent log changes, expressed in percentage points.

perceived wisdom that patent improvement in developing countries tends to generate profit outflows, despite the fact that these profit gains encourage Foreign firms to introduce leading technologies, as discussed later.

Industry Heterogeneity. In Panel B of Table 4, I decompose the changes in the aggregate price index and profits across different industries. The results show substantial industry heterogeneity in the impact of enhanced patent protection. Overall, the decline in aggregate price index is driven by a largest reduction in Chemicals (-0.57 p.p), followed by Metal Products & Machinery (-0.11 p.p) and Electrical Equipment (-0.14 p.p). In contrast, Pharmaceuticals (+0.06 p.p) and Electronics (+0.22 p.p) experience an increase in the price index, reflecting stronger markups in these sectors.

In Figure 7, I provide further breakdown for the relative contributions of Home and Foreign firms to the within-industry changes in price indexes, abstracting away from the overall weight β_j of each industry. Chemicals exhibit the largest divergence between Home and Foreign firms, with Foreign firms contributing a substantial reduction of -6.20 p.p., compared to a mild increase in Home markups (0.16 p.p.). In contrast, Pharmaceuticals display a much stronger increase in Home firms' prices (1.30 p.p.), and Foreign firms show an even larger price inflation (1.71 p.p.). Electronics, another sector with substantial activity from Foreign affiliates, experiences the second largest markup increases for Foreign firms (1.61 p.p.), while Home

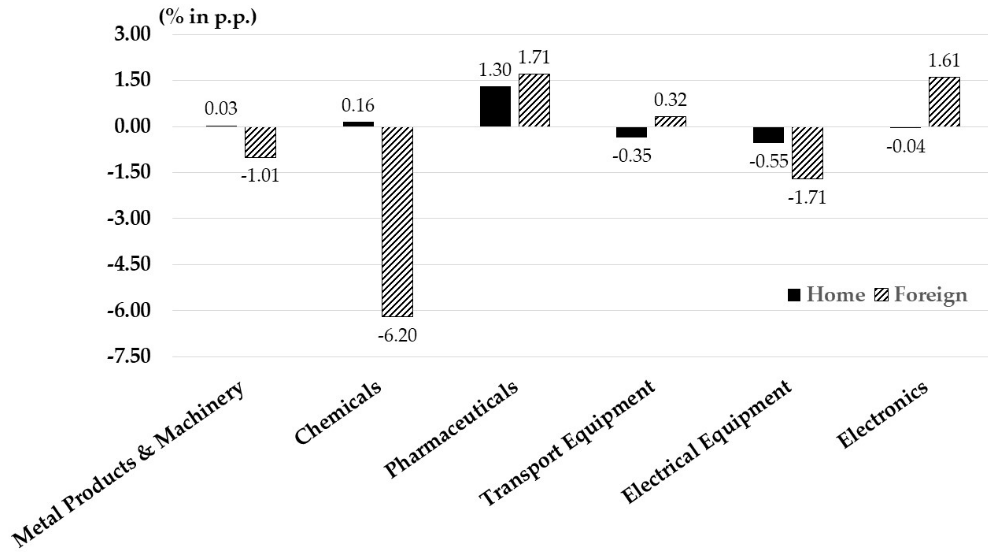


Figure 7: Decomposition of Price Index Changes, $\Delta \ln P_j$

Notes: This figure decomposes the changes of industry-specific price indexes into contributions of Home and Foreign firms. Each bar shows $s^i_j \Delta \ln P^i_j$, where $i \in \{\text{Home}, \text{Foreign}\}$ and $s^i_j = (P^i_j / P_j)^{1-\sigma}$ denotes the market share of firms from country i in industry j. See Appendix C.2 for the derivations of decomposition. All numbers represent log changes, expressed in percentage points.

firms see little change (-0.04 p.p.). These differences across industries confirm the mixed impact of patent protection that balances between increased market power and access to more technologies, with certain sectors, like Chemicals, benefiting from more technology access, while others, like Pharmaceuticals and Electronics, see greater concentration of market power.

The decomposition of profits in Panel B of Table 4 also reveals substantial industry heterogeneity. Specifically, a significant gain in Home profits from the industry of Transport Equipment (up by 10.76 p.p.), while Chemicals (6.13 p.p.) and Metal Products & Machinery (2.52 p.p.) also show notable increases. Foreign firms, on the other hand, gain more evenly across industries, with the highest profit earned in in Electronics (7.35 p.p.), followed by Metal Products & Machinery (5.69 p.p.), highlighting their stronger presence in these industries.

Overall, the results suggest that the 2004 enhancement of patent enforcement in China improved aggregate welfare by both increasing domestic profits and reducing the aggregate price index. However, these impacts are highly heterogeneous across industries. Consumers benefit from the introduction of more Foreign varieties in industries like Chemicals, where the price index decreases, but they face higher price inflation in sectors like Pharmaceuticals and Electronics, where markups rise more significantly.

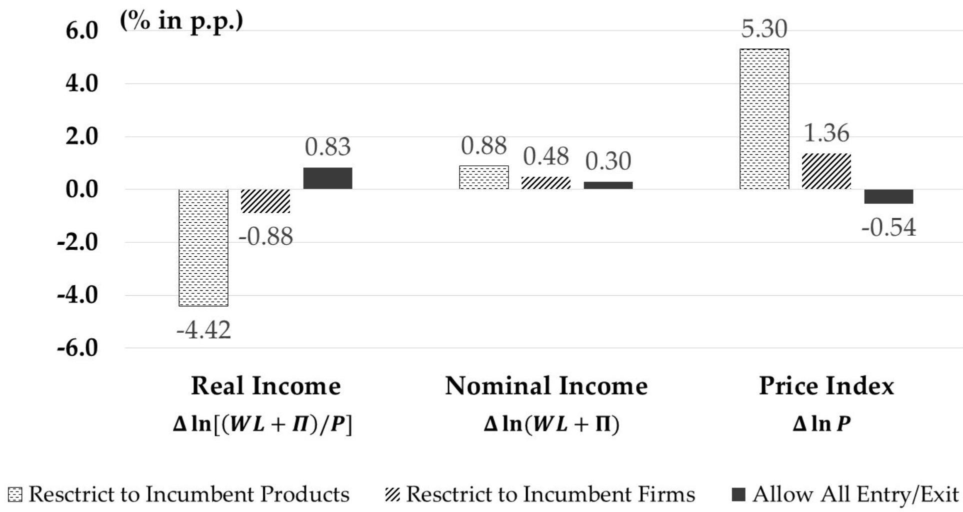


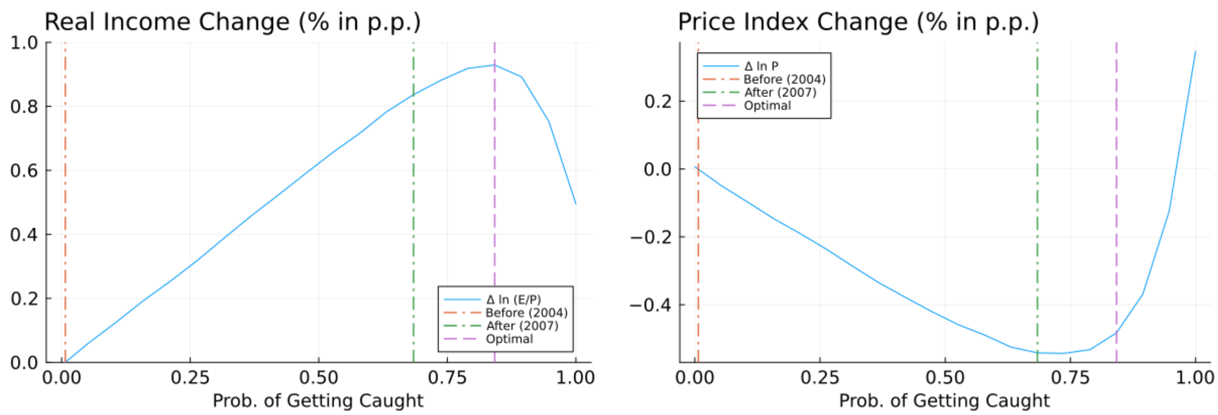
Figure 8: Mechanism Decomposition

Notes: This figure displays the log changes in real income, nominal income, and the price index relative to the status quo, assuming the same level of enhanced patent protection under three different scenarios. In the first scenario, the entry or exit of products and inventors is restricted, i.e., only incumbent products adjust their markups in response to changes in patent protection. In the second scenario, while firm-level entry and exit are restricted, incumbent firms are allowed to introduce new products. In the third scenario, both product and firm entry and exit are unrestricted. All numbers represent log changes, expressed in percentage points.

6.2 Mechanism Decomposition

In Section 4.6, I demonstrate that the aggregate impacts of patent protection can be decomposed into three main mechanisms: (i) increased markups on incumbent products, (ii) the entry of top-quality products that were previously self-excluded by incumbent inventors, and (iii) firm-level entry and exit responses. To quantify the relative strength of these mechanisms, I decompose the aggregate effects documented in Section 6.1 by conducting a series of counterfactual experiments. In each experiment, I vary the patent enforcement parameter δ to the targeted level, applying different restrictions on the entry of new products and the entry and exit of firms. This allows me to isolate the contributions of incumbent products, new product entry, and firm-level extensive-margin adjustments to the overall welfare changes.

Figure 8 shows the results. Restricting the analysis to incumbent products only, without the entry of new products, strengthening patent protection would have significantly reduced real income by 4.42%. This decline is mainly driven by the increased markups on incumbent products, which push the aggregate price index up by 5.3%. Allowing the entry of new products but still restricting firm-level entry and exit would substantially mitigate the welfare loss, with real income decreasing by only 0.88% compared to the status quo. The smaller increase in the aggregate price index, which rises by just 1.36%, accounts for this improvement. Finally, when both product and firm-level entry and exit are permitted, the analysis returns to the baseline



(a) Real Income (b) Price Index

Figure 9: Optimal Patent Protection

Notes: This figure displays the changes of aggregate real income, $\Delta \ln [(WL + \Pi)/P]$, and aggregate price index, $\Delta \ln P$, against the level of patent enforcement. On the horizontal axis, patent enforcement δ is transformed to the probability of an imitator getting caught in the model, $1 - \delta^{-1}$, which varies across zero to one. The vertical line in red represents the status quo, the one in green the protection level after the IPR campaign, and the one in purple the optimal protection level.

case, where the aggregate welfare improves by 0.83%.

The results highlight the within-firm technology selection as a key channel through which patent protection shapes welfare outcomes—even without firm entry and exit, allowing incumbent firms to introduce higher-quality products significantly reduces the negative effects of increased markups. The twice as large impact of within-firm adjustments compared to firm-level entry suggests that the ability of firms to choose which technologies to bring to market is a major factor in determining the overall welfare effects of patent protection. This result also reinforces the importance of my empirical findings—by encouraging firms to bring their best technologies to the market, strengthening patent protection contributes substantially to consumer welfare even in the absence of new firm entry.

6.3 Optimal Patent Protection

The analysis thus far has focused on the effects of a specific patent enforcement enhancement in China. To gain a more comprehensive understanding of the role patent protection plays in shaping welfare of a developing economy, it is natural to analyze the optimal level of patent protection. This subsection conducts a counterfactual analysis to explore the optimal level of patent enforcement that balances the aforementioned trade-offs.

Figure 9 presents the results of the optimal patent protection analysis. In Figure 9a, the log changes in real income are plotted against the probability of an imitator being caught, denoted as $1 - \delta^{-1}$, which represents a transformed measure of the patent enforcement level in the model. The graph reveals an inverted-U shape, where real income initially rises as patent protection is strengthened, reaching a peak when the probability of catching an imitator is about 85%. Beyond this point, further increases in patent enforcement reduce welfare. At the optimal level of protection, aggregate real income is 0.93% higher than the status quo, whereas full protection proves to be sub-optimal, yielding only a 0.5% increase in real income.

The U-shaped curve in Figure 9b, which shows the changes in the aggregate price index, explains the inverted-U shape of real income. At low levels of patent protection, strengthening enforcement predominantly leads to the introduction of new, higher-quality products, which lowers the aggregate price index. However, as patent protection intensifies, the rising markups charged by inventors on incumbent products start to dominate, ultimately pushing the price index higher. The net effect on real income is a balance between the U shape of the price index and the increase in nominal income, resulting in an optimal level of patent protection slightly beyond the point where the price index is at its lowest.

In summary, while increased patent enforcement initially benefits consumers by reducing the price index and increasing access to higher-quality products, there is a threshold beyond which the costs of market power begin to dominate, reducing overall welfare. The analysis also suggests that China's patent protection in 2004 was slightly below the optimal level, and that there is room for improvement without resorting to full protection.

7 Concluding Remarks

In this paper, I analyze the economic impacts of patent protection in developing countries, focusing on the trade-off between market power and access to advanced technologies. Using a policy shock in China in 2004, where patent enforcement was unevenly enhanced across provinces, I document novel empirical findings on how multinational enterprises (MNEs) and domestic inventors respond to changes in patent protection. The empirical evidence shows that stronger patent enforcement leads MNEs to adopt their best technologies in their Chinese affiliates, while domestic inventors also produce higher-quality innovations. However, both groups increase their markups in response to stronger patent protection, indicating that the benefits of technology access come with the social costs of higher prices for consumers.

To rationalize these findings and quantify their welfare implications, I develop a novel partial equilibrium model in which inventors, both foreign and domestic, make endogenous decisions about which technologies to adopt and what markups to charge. The model incorporates patent infringement through imitation, where imperfect patent protection allows imitators to enter the market and compete with patent holders, reducing their markups. Importantly, the model introduces a within-firm technology selection mechanism, where inventors self-select which products to bring to the market based on the level of patent protection. Stronger protection induces firms to introduce their top-quality products but also enables them to raise markups on their entire portfolio. This within-firm selection plays a key role in shaping the aggregate welfare effects of patent protection.

My quantitative analysis reveals that the 2004 IPR enhancement in China was welfare-improving, increasing aggregate real income by 0.83%. The results also highlight significant industry heterogeneity and underscores the importance of within-firm selection of technology adoption in shaping consumer welfare. Counterfactual analyses suggest that the general relationship between patent protection and welfare follows an inverted U-shape, where optimal patent enforcement could raise welfare by around 0.93%, while full protection would be sub-optimal.

This paper can be extended in several directions. First, my model is static and thus excludes dynamic decisions such as research and development (R&D), which is a central focus in much of the IPR literature. Given the context of a developing economy, where access to existing technologies—primarily from foreign firms—is crucial, my framework captures the key policy trade-off: incentivizing the adoption of advanced technologies while preventing excessive increases in consumer prices. Nonetheless, incorporating this model into a dynamic framework could shed light on how this trade-off interacts with long-term economic growth. Second, my analysis abstracts from knowledge spillovers, another potential policy benefit of stimulating multinational production. If more granular microdata were available to identify knowledge spillovers from foreign to domestic inventors, it could significantly deepen our understanding of patent protection policies.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Ang, James S, Yingmei Cheng, and Chaopeng Wu, "Does Enforcement of Intellectual Property Rights Matter in China? Evidence from Financing and Investment Choices in the High-Tech Industry," *Review of Economics and Statistics*, 2014, *96* (2), 332–348.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Bai, Jie, Panle Barwick, Shengmao Cao, and Shanjun Li, "Quid Pro Quo, Knowledge Spillover, and Industrial Quality Upgrades: Evidence from the Chinese Auto Industry," 2023.

Bernard, Andrew B., Stephen J. Redding, and Peter K. Schott, "Multiproduct Firms and Trade Liberalization," *The Quarterly Journal of Economics*, August 2011, *126* (3), 1271–1318.

Bilir, L Kamran, "Patent Laws, Product Life-Cycle Lengths, and Multinational Activity," *American Economic Review*, 2014, *104* (7), 1979–2013.

Blank, Rebecca M, David J Kappos, M Doms, S Graham, B Bond, G Hancock, J Burston, D Langdon, and F Yu, "Intellectual Property and the US Economy: Industries in Focus," *Economics and Statistics Administration: Washington, DC, USA*, 2012.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang, "WTO Accession and Performance of Chinese Manufacturing Firms," *American Economic Review*, 2017, *107* (9), 2784–2820.

Branstetter, Lee and Kamal Saggi, "Intellectual Property Rights, Foreign Direct Investment and Industrial Development," *The Economic Journal*, 2011, *121* (555), 1161–1191.

Branstetter, Lee G, Raymond Fisman, and C Fritz Foley, "Do Stronger Intellectual Property Rights Increase International Technology Transfer? Empirical Evidence from US Firm-Level Panel Data," *The Quarterly Journal of Economics*, 2006, *121* (1), 321–349.

Branstetter, Lee, Ray Fisman, C. Fritz Foley, and Kamal Saggi, "Does intellectual property rights reform spur industrial development?," *Journal of International Economics*, January 2011, *83* (1), 27–36.

Brooks, Wyatt J, Joseph P Kaboski, and Yao Amber Li, "Agglomeration, Misallocation, and (the Lack of) Competition," *American Economic Journal: Macroeconomics*, 2021, *13* (4), 483–519.

Bryan, Kevin A and Heidi L. Williams, "Innovation: Market Failures and Public Policies," in "Handbook of Industrial Organization," Vol. 5, Elsevier, 2021, pp. 281–388.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu, "Notching R&D Investment with Corporate Income Tax Cuts in China," *American Economic Review*, 2021, *111* (7), 2065–2100.

De Ridder, Maarten, Basile Grassi, and Giovanni Morzenti, "The Hitchhiker's Guide to Markup Estimation: Assessing Estimates from Financial Data," 2024.

Ding, Xuedong and Jun Li, *Incentives for Innovation in China: Building an Innovative Economy*, Routledge, 2015.

European Patent Office, "PATSTAT Global 2023 Autumn Edition," 2023. Accessed: 2023-12.

Fan, Jingting, "Talent, Geography, and Offshore R&D," *Review of Economic Studies*, 2024, p. rdae044.

Ginarte, Juan C. and Walter G. Park, "Determinants of patent rights: A cross-national study," *Research Policy*, October 1997, *26* (3), 283–301.

Glass, Amy Jocelyn and Xiaodong Wu, "Intellectual Property Rights and Quality Improvement," *Journal of Development Economics*, 2007, *82* (2), 393–415.

Grossman, Gene M and Edwin L-C Lai, "International Protection of Intellectual Property," *American Economic Review*, 2004, *94* (5), 1635–1653.

Hémous, David, Simon Lepot, Thomas Sampson, and Julian Schärer, "Trade, Innovation and Optimal Patent Protection," 2023.

Holmes, Thomas J, Ellen R McGrattan, and Edward C Prescott, "Quid Pro Quo: Technology Capital Transfers for Market Access in China," *The Review of Economic Studies*, 2015, *82* (3), 1154–1193.

Ivus, Olena, "Do Stronger Patent Rights Raise High-Tech Exports to the Developing World?," *Journal of International Economics*, 2010, *81* (1), 38–47.

König, Michael, Kjetil Storesletten, Zheng Song, and Fabrizio Zilibotti, "From Imitation to Innovation: Where is All that Chinese R&D Going?," *Econometrica*, 2022, *90* (4), 1615–1654.

Lai, Edwin L-C, "International Intellectual Property Rights Protection and the Rate of Product Innovation," *Journal of Development Economics*, 1998, *55* (1), 133–153.

Lai, Huiwen, Keith E Maskus, and Lei Yang, "Intellectual Property Enforcement, Exports and Productivity of Heterogeneous Firms in Developing Countries: Evidence from China," *European Economic Review*, 2020, *123*, 103373.

Lam, Leo C H, "Equilibrium IPR Protections, Innovation and Imitation in A Globalized World," 2024.

Loecker, Jan De and Frederic Warzynski, "Markups and Firm-Level Export Status," *American economic review*, 2012, *102* (6), 2437–2471.

Ma, Xiao and Yiran Zhang, "How do Multinationals Impact China's Technology? The Role of Quid Pro Quo Policy and Technology Spillovers," 2024.

Maskus, Keith E, *Intellectual Property Rights in the Global Economy*, Institute for International Economics, 2000.

Melitz, Marc J, "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Park, Walter G., "International Patent Protection: 1960–2005," *Research Policy*, May 2008, *37* (4), 761–766.

Qian, Yi, "Impacts of Entry by Counterfeiters," *The Quarterly Journal of Economics*, 2008, *123* (4), 1577–1609.

Santacreu, Ana Maria, "Dynamic Gains from Trade Agreements with Intellectual Property Provisions," 2023.

Shimomura, Ken-Ichi and Jacques-François Thisse, "Competition among the Big and the Small," *The Rand Journal of Economics*, 2012, *43* (2), 329–347.

Yang, Guifang and Keith E Maskus, "Intellectual Property Rights, Licensing, and Innovation in an Endogenous Product-Cycle Model," *Journal of International Economics*, 2001, *53* (1), 169–187.

Appendix A Data and Empirical Evidence

I discuss the details of the reduced-form evidence in this section. Section A.1 explains the data sources, dataset construction and cleaning procedures. Section A.2 introduces the patent-intensive industries. Section A.3 discusses the procedure to structurally estimate firm-level markups. Finally, Section A.4 presents the details of the regression results and additional robustness checks.

A.1 Dataset Construction

I assemble a dataset focusing on the production and patenting activities of manufacturing firms in China, which includes domestic Chinese firms and multinational enterprises (MNEs) with production affiliates in China. This subsection introduces the data sources and the procedure to construct the final dataset.

Production Data. The analysis centers on Chinese manufacturing firms in the Annual Survey of Industrial Enterprise, maintained by the National Bureau of Statistics of China (NBSC). This dataset covers all state-owned enterprises and non-state-owned firms with annual sales exceeding 5 million RMB from 1998 to 2014. It provides comprehensive accounting and production information, including firm identity, ownership, location, main industry classification, revenue, employment, fixed assets, and expenditure on intermediate inputs.

To link each firm consistently over time, I employ a procedure following Brandt et al. (2017) to create a unique identifier. The algorithm establishes firm linkages over time using information on the NBS ID, firm name, the name of legal person representative, phone number, address, name of main products, founding year, etc. During the period, the majority of firms in the dataset operate as single-plant entities within a single province and primarily engage in one main industry.

As discussed in Brandt et al. (2017), the production data after 2007 contain a lot of missing or misreported values. Hence, for the empirical analysis and markup estimation, I focus on the period from 2002 (after China joined the WTO) to 2007. When merging with patent data, however, I utilize the information of firms' identity for the whole sample from 1998-2014.

Patent Data. I link the NBSC Database to patent data provided by China's State Intellectual Property Office (SIPO). This link is established by exactly matching the firms' names (in Chinese). For each patent filed by the firm, I further establish link with the citation data from PATSTAT by matching the unique patent application number with that of the citing patent.

Matching patent application numbers across the two datasets requires careful investigation of changes in application numbering between different vintages. As illustrated in Figure A.1, a new phase in the patent application numbering system was introduced in October 2003. Before this phase, each patent application was assigned a unique 9-digit identifier that included the

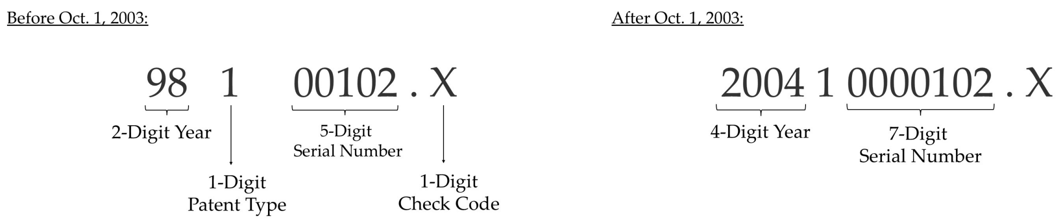


Figure A.1: Concordance of Chinese Patent Application ID

Notes: This figure illustrates the vintage changes in Chinese patent application IDs, which are used to merge Chinese firm-level production data with patent data from PATSTAT and Orbis. The first two or four digits of the patent code represents the patent application year, followed by one digit indicating the patent type: "1" for inventions, "2" for utility models, "3" for designs, "8" for international invention patent applications, and "9" for international utility model applications. The following five or seven digits indicate the serial number of applications for that year, and the final digit after the decimal point is a computer-generated check code. The example shows the application ID of the 102nd invention patent for the years 1998 and 2004.

year of application, patent type, and a unique serial number. In the post-2003 phase, each application number expanded to a 13-digit format, retaining the same core information but with additional digits. I manually decompose the application numbers from both vintages into their constituent parts—the application year, patent type, and unique serial number—and use these components to match records with their counterparts in PATSTAT. In line with the paper's focus and the policy shock, I focus only on invention patents.

To mitigate the concern on missing patents in the match with the SIPO dataset, I supplement with patents in PATSTAT applied by exactly the same firm. This increases the number of patents from 1,987,313 to 2,810,083 (a nearly 30% increase). Together, this approach enables me to comprehensively observe the annual number of patents filed by each firm in the NBSC dataset from 1980 onwards, as well as the forward citations received by each patent.

Global Patent Portfolio of MNEs. To investigate how multinational enterprises (MNEs) adjust their patenting strategies in China in response to local patent protection, I integrate the NBSC data with the Orbis Intellectual Property Database, as used in Fan (2024). To my knowledge, this paper is the first to combine these two datasets.

The integration process begins by matching patent identifiers. First, each MNE patent in Orbis is linked to its patent family in PATSTAT. Each patent family consists of applications filed across different patent offices, typically covering a single product or technology. Second, I match the Chinese patents filed by MNE affiliates from the NBSC data to their respective patent families, establishing a link between the foreign affiliate in China and its global headquarters. This process allows me to define the global patent portfolio of the multinational firm as the set of technologies potentially available for adoption by the Chinese affiliate.

Patent Quality. Following established methodologies in the literature (e.g., Bryan and Williams, 2021), I use forward citations as a proxy for patent quality. Specifically, for a patent ω invented in year $t(\omega)$ and receiving forward citations $\psi(\omega)$, its quality is defined as $\varphi(\omega) \equiv \psi(\omega)/\bar{\psi}_{t(\omega)}$, where $\bar{\psi}_{t(\omega)}$ represents the average number of citations received by all patents globally invented in the same year. This adjustment accounts for the trend that more recent patents tend to receive fewer citations, thus enabling inter-temporal comparisons.

A.2 Patent-Intensive Industries

In this paper, I focus on patent-intensive industries. Following the USPTO report (Blank et al., 2012), I calculate an industry-level patent intensity measure as:

$$\text{Patent Intensity}_j = \frac{\text{Number of Patents}_j}{\text{Total Employments}_j},$$

for each 2-digit ISIC (Rev. 4) industry j using 2004 data. I then select industries with an above-median patent intensity measure, excluding those with total patent number below 1000. This yields nine industries of interest, listed in Table A.1.

Table A.1: Patent-Intensive Industries

ISIC	Industry	Patent Number (thousand)	Employment (million)	Patent Intensity
27	Electrical Equipment	32.23	8.39	3.80
26	Computer, Electronic and Optical Products	32.81	10.45	3.10
21	Basic Pharmaceutical Products	3.93	3.20	1.20
30	Other Transport Equipment	3.55	4.21	0.80
20	Chemicals and Chemical Products	8.79	10.90	0.80
28	Machinery and Equipment N.E.C.	7.03	12.15	0.60
32	Medical and Dental Instruments	2.10	5.09	0.40
29	Motor Vehicles, Trailers and Semi-Trailers	1.77	5.18	0.30
25	Fabricated Metal Products	1.23	7.00	0.20

Notes: This table lists all patent intensive industries, as defined by those with above-median ratio of total patents to total employments and total patent number exceeding 1,000 in 2004.

A.3 Markup Estimation

My analysis on firms' market power rely on an empirical measurement of firms' markups. In the data, I do not have direct measures of markups without observing prices and marginal costs. Instead, I follow a common approach in the literature to structurally estimate firm-level markups using the method of De Loecker and Warzynski (2012). This subsection introduces the estimation procedure.

The method of De Loecker and Warzynski (2012) relies on a first-order condition of the costminimization problem faced by a producer f, who chooses at least one variable input free of adjustment costs. I use intermediate materials that are observed in data as this flexibly chosen production factor. The first-order condition for intermediate inputs, which I denote as $\mathfrak{m}_f$, can be written as

$$p_{ft}^{\mathfrak{m}} = \lambda_{ft} \frac{\partial x_{ft}(\cdot)}{\partial \mathfrak{m}_{ft}}, \tag{A.1}$$

where $p_{ft}^{\mathfrak{m}}$ is the input price for materials, λ_{ft} is the marginal cost of production at a given level of output, $x_{ft}(\cdot)$ is the production function, and t is a year.

Rearranging (A.1) yields

$$\frac{\partial x_{ft}(\cdot)}{\partial \mathfrak{m}_{ft}} \frac{\mathfrak{m}_{ft}}{x_{ft}} = \frac{1}{\lambda_{ft}} \frac{p_{ft}^{\mathfrak{m}} \mathfrak{m}_{ft}}{x_{ft}}, \tag{A.2}$$

which further implies that

$$\mu_{ft} \equiv \frac{p_{ft}}{\lambda_{ft}} = \frac{\partial \ln x_{ft}(\cdot)}{\partial \ln \mathfrak{m}_{ft}} \times \left[\frac{p_{ft}^{\mathfrak{m}} \mathfrak{m}_{ft}}{x_{ft}} \right]^{-1}, \tag{A.3}$$

where the first term is the output elasticity on material input, and the second term in the square bracket is the expenditure shares on intermediate inputs in total sales. Since the expenditure shares are observed in data, it remains to estimate the output elasticity by estimating the production function.

The production function I estimate is given by

$$\ln x_{ft} = \mathbf{f}(\ln k_{ft}, \ln l_{ft}, \ln \mathfrak{m}_{ft}; \vec{\beta}_j) + \ln z_{ft} + \epsilon_{ft}. \tag{A.4}$$

Following Brooks, Kaboski and Li (2021), I presume that the gross production function is a third-order translog function in capital, labor, and materials, which gives

$$\begin{aligned} \ln x_{ft} = {} & \beta_j^k \ln k_{ft} + \beta_j^l \ln l_{ft} + \beta_j^{\mathfrak{m}} \ln \mathfrak{m}_{ft} + \beta_j^{kk} (\ln k_{ft})^2 + \beta_j^{kl} (\ln k_{ft} \ln l_{ft}) \\ & + \beta_j^{k\mathfrak{m}} \ln(\ln k_{ft} \mathfrak{m}_{ft}) + \beta_j^{ll} (\ln l_{ft})^2 + \beta_j^{l\mathfrak{m}} \ln(\ln l_{ft} \mathfrak{m}_{ft}) \\ & + \beta_j^{k\mathfrak{m}} \ln(\ln k_{ft} \mathfrak{m}_{ft}) + \beta_j^{\mathfrak{m}\mathfrak{m}} (\ln \mathfrak{m}_{ft})^2 + \beta_j^{kkk} (\ln k_{ft})^3 + ... + \ln z_{ft} + \epsilon_{ft}. \end{aligned} \tag{A.5}$$

I assume that $\vec{\beta}_j$ is industry-specific and estimate them separately for each 2-digit industry.

The estimation procedure follows Ackerberg, Caves and Frazer (2015) and consists of two steps. In the first step, I run nonparametrically

$$\ln x_{ft} = \Phi_t(\ln k_{ft}, \ln l_{ft}, \ln \mathfrak{m}_{ft}) + \epsilon_{ft} \tag{A.6}$$

and obtain estimates for Φ_{ft} and ϵ_{ft}. This step enables us to express the logged-productivity $\ln z_{ft}$ as a function of $\widehat{\Phi}_{ft}$ and $\mathbf{f}(\ln k_{ft}, \ln l_{ft}, \ln \mathfrak{m}_{ft}; \vec{\beta}_j)$ for any guessed vector of $\vec{\beta}_j$.

By assuming that the logged-productivity $\ln z_{ft}$ follows a first-order Markov process:

$$\ln z_{ft} = \mathbf{g}\left(\ln z_{f,t-1}\right) + \xi_{ft}, \tag{A.7}$$

we could use GMM to estimate $\vec{\beta}_j$. This final step requires a set of instruments, where I include capital, logged labor, logged materials and their interaction terms. With $\vec{\beta}_j$ estimated, the output elasticity on intermediate inputs can be readily calculated, which gives an estimate of the firm-level markups.

A common limitation of using Chinese firm-level data to estimate markups is the lack of quantity information in the data. To mitigate this issue, I follow Brandt, Van Biesebroeck, Wang and Zhang (2017) and use a set of price deflators on both revenue for output and fixed assets for capital inputs. Still, when revenue is used to estimate the production function, the estimated output elasticity can still be biased by the price-elasticity of demand. However, as De Ridder, Grassi and Morzenti (2024) point out in a recent paper, even if the levels of markups may not be consistently estimated, the trends in markups and the dispersion of markups across firms can still be well-measured. Since my analysis of markup response to patent enforcement essentially reflects the within-firm changes across time and the across-firm variations within province-industry, I believe that such bias resulting from the lack of quantity data is not crucial to my results.

A.4 Details on Reduced-Form Results

This subsection reports the detail results of my reduced-form analysis in Section 3. Table A.2 presents the results for Figure 3, Table A.3 presents the results for Figure 4, and Table A.4 presents the results for Figure 5.

Table A.2: MNE's Increased Willingness in Technology Adoption (Results in Figure 3)

	Share of Patent Families with A Chinese Patent, $\mathcal{S}_{ft}$(p.p.)				
	Below 25%	25% $\sim$ 50%	50% $\sim$ 75%	Above 75%	Above 90%
	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}\left[l(f) \text{ is treated}\right] \times \mathbb{I}\left[t = 2002\right]$	2.006	-5.834	-3.882	-0.915	3.677
	(4.687)	(5.061)	(2.728)	(5.065)	(6.462)
$\mathbb{I}\left[l(f) \text{ is treated}\right] \times \mathbb{I}\left[t = 2003\right]$	2.728	-2.077	4.466	2.456	1.658
	(3.384)	(4.766)	(3.593)	(4.423)	(6.353)
$\mathbb{I}\left[l(f) \text{ is treated}\right] \times \mathbb{I}\left[t = 2005\right]$	-0.714	0.822	1.921	9.551**	13.654**
	(3.363)	(3.926)	(4.356)	(3.771)	(5.375)
$\mathbb{I}\left[l(f) \text{ is treated}\right] \times \mathbb{I}\left[t = 2006\right]$	1.404	-0.026	2.923	9.320**	18.522***
	(3.206)	(4.364)	(3.807)	(3.916)	(5.568)
$\mathbb{I}\left[l(f) \text{ is treated}\right] \times \mathbb{I}\left[t = 2007\right]$	3.529	-6.164	3.352	10.722**	14.844**
	(3.148)	(4.470)	(5.350)	(4.351)	(5.648)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm-Year Control X_{ft}	Yes	Yes	Yes	Yes	Yes
Observations	2150	1208	1577	1439	1081
R^2	0.846	0.799	0.787	0.823	0.807

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the regression coefficients shown in Figure 3, examining how enhanced patent enforcement influences MNEs' willingness to adopt technologies in China. The regression specification is detailed in Equation (2). The dependent variable, $\mathcal{S}_{ft}$, represents the share (in percentage points) of globally invented patent families that include a Chinese patent. Each column calculates $\mathcal{S}_{ft}$ based on patents of varying quality, grouped by quality percentile within MNE f's global patent portfolio for year t. Patent quality is defined as the forward citation counts demeaned by all patents filed in the same year. The variable $l(f)$ denotes the province where f's Chinese affiliate is located. Standard errors are clustered at the province-year level, and industries are classified by 2-digit ISIC (Rev. 4). Control variables X_{ft} include log employment, log patent stock, log provincial-level GDP, and a firm-year time trend.

Table A.3: Increased Innovation by Domestic Firms (Results in Figure 4)

	$\mathbb{I}[N_{ft} > 0]$	$\mathbb{I}[N_{ft}^{US/EP/JP} > 0 \mid N_{ft} > 0]$	$\bar{\varphi}_{ft}$
	(1)	(2)	(3)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[t = 2002]$	-0.010	0.027	0.005
	(0.011)	(0.048)	(0.029)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[t = 2003]$	-0.006	0.026	-0.000
	(0.006)	(0.035)	(0.016)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[t = 2005]$	-0.009*	0.066**	0.014
	(0.005)	(0.031)	(0.012)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[t = 2006]$	0.019**	0.056**	0.020
	(0.008)	(0.025)	(0.015)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[t = 2007]$	0.022***	0.054	0.032**
	(0.007)	(0.033)	(0.016)
Firm Fixed Effects	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes
Firm-Year Control X_{ft}	Yes	Yes	Yes
Observations	67878	3126	10875
R^2	0.444	0.647	0.903

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the regression coefficients shown in Figure 4, examining how affects domestic firms' innovation activities. The regression specification is detailed in Equation (2). In Column (1), the dependent variable is an indicator variable that equals one if Chinese firm f file a patent in year t. Column (2) explores the quality of the new patents, taking the propensity to file a triadic patent, i.e., patent that is granted by USPTO, EPO, or JPO, a common indicator for high-quality patent. Column (3) regresses the average patent quality of firm f in year t, with quality $\varphi(\omega)$ defined as the forward citation counts demeaned by all patents filed in the same year. The variable $l(f)$ denotes the province where f is located. Standard errors are clustered at the province-year level, and industries are classified by 2-digit ISIC (Rev. 4). Control variables X_{ft} include log employment, log patent stock, log provincial-level GDP, and a firm-year time trend.

Table A.4: Increased Markup in Response to Patent Enforcement (Results in Figure 5)

$\ln \mu_{ft}$	(1) $\times\mathbb{I}\,[t = 2002]$	(2) $\times\mathbb{I}\,[t = 2003]$	(3) $\times\mathbb{I}\,[t = 2005]$	(4) $\times\mathbb{I}\,[t = 2006]$	(5) $\times\mathbb{I}\,[t = 2007]$
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[f$ is Dom. Pat.$]$	-0.001	-0.002	0.008	0.017**	0.022***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.008)
$\mathbb{I}\,[l(f)$ is treated$] \times \mathbb{I}\,[f$ is Foreign$]$	-0.000	-0.005	0.006	0.002	0.011*
	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)
Firm Fixed Effects			Yes		
Province-Industry-Year Fixed Effects			Yes		
Category-Year Fixed Effects X_{ft}			Yes		
Observations			560842		
R^2			0.561		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the regression coefficients presented in 5, analyzing the impact of enhanced patent enforcement on the markups of domestic patent holders and foreign affiliates. The regression specification follows a triple-diff-in-diff design, detailed in Equation (3). Each row corresponds to a category of firms—either domestic patent holders or foreign affiliates—with each cell reporting the coefficient of the interaction between the province × category term (specific to each row) and the year dummy (specific to each column). Year 2004 is omitted and taken as the baseline. Standard errors are clustered at the province-year level, and industries are categorized by 2-digit ISIC (Rev. 4).

Appendix B Theory

B.1 Derivation of Inventor's Optimal Pricing

Given labor productivity z_f, an inventor face demand (7) for product (ϕ, z_f):

$$x_j^I(\phi, z_f) = \phi \cdot \left(\frac{p_j^I(\phi, z_f)}{p_j(\phi, z_f)}\right)^{-\eta} \left(\frac{p_j(\phi, z_f)}{P_j}\right)^{-\sigma} X_j,$$

where

$$p_j(\phi, z_f) = \left[p_j^I(\phi, z_f)^{1-\eta} + p_j^M(\phi, z_f)^{1-\eta}\right]^{\frac{1}{1-\eta}}.$$

Competition in Price. Suppose the inventor compete with imitators by setting price:

$$\max_{p_j^I(\phi, z_f)} \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \cdot x_j^I(\phi, z_f),$$

subject to the demand above. The first-order condition requires that

$$0 = x_j^I(\phi, z_f) + \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \frac{\mathrm{d}x_j^I(\phi, z_f)}{\mathrm{d}p_j^I(\phi, z_f)}$$

$$\Rightarrow \frac{p_j^I(\phi, z_f) - \frac{W}{z_f}}{p_j^I(\phi, z_f)} = -\left[\frac{\mathrm{d}x_j^I(\phi, z_f)/x_j^I(\phi, z_f)}{\mathrm{d}p_j^I(\phi, z_f)/p_j^I(\phi, z_f)}\right]^{-1} = \left[-\frac{\mathrm{d}\ln x_j^I(\phi, z_f)}{\mathrm{d}\ln p_j^I(\phi, z_f)}\right]^{-1} \equiv \varepsilon_j^I(\phi, z_f)^{-1}.$$

To solve for this, notice that

$$\ln x_j^I(\phi, z_f) = \ln \phi - \eta \ln p_j^I(\phi, z_f) + (\eta - \sigma) \ln p_j(\phi, z_f) + \ln(P_j^\sigma X_j),$$

which gives the effective elasticity of substitution

$$\varepsilon_j^I(\phi, z_f) \equiv -\frac{\mathrm{d}\ln x_j^I(\phi, z_f)}{\mathrm{d}\ln p_j^I(\phi, z_f)} = \eta - (\eta - \sigma) \cdot s_j^I(\phi, z_f) = s_j^I(\phi, z_f) \cdot \sigma + \left[1 - s_j^I(\phi, z_f)\right] \cdot \eta,$$

where the inventor's *within-product* market share

$$s_j^I(\phi, z_f) = \frac{p_j^I(\phi, z_f)^{1-\eta}}{p_j(\phi, z_f)^{1-\eta}} = \frac{p_j^I(\phi, z_f)^{1-\eta}}{p_j^I(\phi, z_f)^{1-\eta} + p_j^M(\phi, z_f)^{1-\eta}}.$$

Competition in Quantity. If the inventor competes with inventors by setting quantity:

$$\max_{x_j^I(\phi, z_f)} \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \cdot x_j^I(\phi, z_f),$$

it can be shown that the effective elasticity of substitution would be

$$\varepsilon_j^I(\phi, z_f) = \left(s_j^I(\phi, z_f) \cdot \sigma^{-1} + \left[1 - s_j^I(\phi, z_f)\right] \cdot \eta^{-1}\right)^{-1}.$$

B.2 Proof of Proposition 1

Consider an imitator with labor productivity z_m that imitates product (ϕ, z_f) and survives the patent enforcement. With the optimal pricing decisions derived, the equilibrium variable profits in (15) of this imitator can be rewritten as

$$\pi_j^m(\phi, z_f, z_m) = \tilde{\eta} \cdot W^{1-\eta} P_j^{\sigma} X_j \cdot p_j(\phi, z_f)^{\eta-\sigma} \cdot \phi \cdot z_m^{\eta-1}, \tag{B.1}$$

where $\tilde{\eta} \equiv (\eta - 1)^{\eta-1} / \eta^{\eta}$.

Upon entry, the imitator incurs the fixed imitation costs before learning its labor productivity and the realization of patent enforcement. Therefore, its entry decision is made based on the expected profits

$$\begin{aligned} \Pi_j^m(\phi, z_f) &= \delta^{-1} \int_0^{+\infty} \cdot \pi_j^m(\phi, z_f, z_m) \mathrm{d}G_z(z_m) - WF_j^M \\ &= \delta^{-1} \cdot \tilde{\eta} \cdot W^{1-\eta} P_j^{\sigma} X_j \cdot p_j(\phi, z_f)^{\eta-\sigma} \cdot \phi \cdot \tilde{z}_j^{\eta-1} - WF_j^M, \end{aligned} \tag{B.2}$$

where $\tilde{z}_j \equiv \left[\int_0^{+\infty} z_m^{\eta-1} \mathrm{d}G_{z,j}(z_m) \right]^{\frac{1}{\eta-1}}$.

When $\Pi_j^m(\phi, z_f) < 0$, the product is not imitated, and $M_j(\phi, z_f) = 0$,

$$p_j(\phi, z_f) = \frac{\sigma}{\sigma - 1} \cdot \frac{W}{z_f}.$$

When $M_i > 0$, imitators enter until $\Pi_j^m(\phi, z_f) = 0$,

$$p_j(\phi, z_f)^{\eta-\sigma} = \frac{\delta}{\phi} \cdot \frac{WF_j^M}{\tilde{\eta} \cdot W^{1-\eta} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}},$$

which can be rearranged into

$$p_j(\phi, z_f) = \frac{\sigma}{\sigma - 1} \cdot \frac{W}{z_f} \cdot \left[\frac{1}{\phi} \cdot \frac{\delta \cdot WF_j^M \cdot z_f^{\eta-\sigma}}{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}} \right]^{\frac{1}{\eta-\sigma}}$$

Therefore, in equilibrium, $\Pi_j(\phi, z_f) \leq 0$ and $M_i \geq 0$ *with complementary slackness*, and

$$p_j(\phi, z_f) = \frac{\sigma}{\sigma - 1} \cdot \frac{W}{z_f} \cdot \min \left\{ 1, \quad \left[\frac{\hat{\phi}_j(z_f)}{\phi} \right]^{\frac{1}{\eta-\sigma}} \right\}, \tag{B.3}$$

where the *firm-specific* quality cutoff for imitation

$$\hat{\phi}_j(z_f) \equiv \underbrace{\frac{WF_j^M}{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}}}_{\equiv \chi_j} \cdot \delta \cdot z_f^{\eta-\sigma}. \tag{B.4}$$

B.3 Proof of Lemma 1

The inventor's variable profit from (ϕ, z_f) depends on whether the product is imitated or not.

When $M_j(\phi, z_f) = 0$, i.e., the product is not imitated, the inventor remains the monopoly of this product, and thus charges a monopolistic markup $\sigma/(\sigma-1)$. This gives a standard result for the variable profit:

$$
\begin{aligned}
\pi_j^I(\phi, z_f) &= \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \cdot \phi \cdot \left(\frac{p_j^I(\phi, z_f)}{P_j}\right)^{-\sigma} X_j \\
&= \tilde{\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot z_f^{\sigma-1} \cdot \phi,
\end{aligned}
$$

with $\tilde{\sigma} \equiv (\sigma-1)^{\sigma-1}/\sigma^{\sigma}$.

When $M_j(\phi, z_f) > 0$, i.e., the product is imitated, imitators enter until

$$
p_j(\phi, z_f)^{\eta-\sigma} = \frac{\delta}{\phi} \cdot \frac{WF_j^M}{\tilde{\eta} \cdot W^{1-\eta} P_j^{\sigma} X_j \cdot \tilde{z}^{\eta-1}}.
$$

The variable profit for inventor becomes

$$
\begin{aligned}
\pi_j^I(\phi, z_f) &= \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \cdot \phi \cdot \left(\frac{p_j^I(\phi, z_f)}{p_j(\phi, z_f)}\right)^{-\eta} \cdot \left(\frac{p_j(\phi, z_f)}{P_j}\right)^{-\sigma} X_j \\
&= \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta} \cdot W^{1-\eta} P_j^{\sigma} X_j \cdot z_f^{\eta-1} \cdot \phi \cdot p_j(\phi, z_f)^{\eta-\sigma} \\
&= \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta} \cdot \frac{\delta \cdot WF_j^M}{\tilde{\eta} \cdot \tilde{z}^{\eta-1}} \cdot z_f^{\eta-1} \\
&= \kappa_j(\phi, z_f) \cdot \delta \cdot WF_j^M \cdot \left(z_f/\tilde{z}_j\right)^{\eta-1},
\end{aligned}
$$

where

$$
\kappa_j(\phi, z_f) \equiv \tilde{\eta}^{-1} \cdot \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta}.
$$

It can be shown that $\kappa_j(\phi, z_f)$ is increasing and concave in $\phi \in (\hat{\phi}_j(z_f), +\infty)$. In particular, when $\phi = \hat{\phi}_j(z_f)$, $\mu_j^I(\phi, z_f) = \sigma/(\sigma-1)$, and

$$
\kappa_j(\hat{\phi}_j(z_f), z_f) = \tilde{\eta}^{-1} \cdot \left[\frac{\sigma}{\sigma-1} - 1\right] \left(\frac{\sigma}{\sigma-1}\right)^{-\eta} = \frac{(\sigma-1)^{\eta-1}/\sigma^{\eta}}{(\eta-1)^{\eta-1}/\eta^{\eta}} \equiv \kappa_{\min} < 1.
$$

When $\phi \to +\infty$, $\mu_j^I(\phi, z_f) \to \eta/(\eta-1)$, and

$$
\lim_{\phi \to +\infty} \kappa_j(\phi, z_f) = \tilde{\eta}^{-1} \cdot \left[\frac{\eta}{\eta-1} - 1\right] \left(\frac{\eta}{\eta-1}\right)^{-\eta} = 1.
$$

This completes the proof.

B.4 Proof of Proposition 2

By Lemma 1, for a given z_f and $\phi > \hat{\phi}_j(z_f)$, since $M_j(\phi, z_f) > 0$,

$$\begin{aligned}
\pi_j^I(\phi, z_f) &= \delta \cdot WF_j^M \cdot \left(z_f/\tilde{z}_j\right)^{\eta-1} \cdot \kappa_j(\phi, z_f) \\
&= P_j(\phi, z_f)^{\eta-\sigma} \cdot \phi \cdot \tilde{\eta} \cdot W^{1-\eta} P_j^\sigma X_j \cdot \tilde{z}^{\eta-1} \cdot \left(z_f/\tilde{z}_j\right)^{\eta-1} \cdot \tilde{\eta}^{-1} \cdot \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta} \\
&= \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \left(\frac{p_j^I(\phi, z_f)}{p_j(\phi, z_f)}\right)^{-\eta} \left(\frac{p_j(\phi, z_f)}{P_j}\right)^{-\sigma} X_j \cdot \phi \\
&= \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] \left(\frac{p_j^I(\phi, z_f)}{p_j(\phi, z_f)}\right)^{\sigma-\eta} \left(\frac{p_j^I(\phi, z_f)}{P_j}\right)^{-\sigma} X_j \cdot \phi \\
&< \left[p_j^I(\phi, z_f) - \frac{W}{z_f}\right] p_j^I(\phi, z_f)^{-\sigma} \cdot P_j^\sigma X_j \cdot \phi \\
&= \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot z_f^{\sigma-1} \cdot \phi \\
&\leq \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot z_f^{\sigma-1} \cdot \phi.
\end{aligned}$$

The first inequality uses the fact that the within-product market share of the inventor is strictly smaller than one due to imitation. The second inequality is a standard profit maximization result—the optimal markup should be $\sigma/(\sigma-1)$ if the inventor is a monopoly of its product. This implies that for all ϕ,

$$\pi_j^I(\phi, z_f) \leq \bar{\pi}_j^I(\phi, z_f) \equiv \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot z_f^{\sigma-1} \cdot \phi.$$

Hence, for any given α_f, there exists a labor productivity cutoff

$$\underline{z}_j(\alpha_f) \equiv \left[\frac{W \cdot \alpha_f}{\tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j}\right]^{\frac{1}{\sigma-1}}.$$

such that whenever $z_f \leq \underline{z}_j(\alpha_f)$,

$$\pi_j^I(\phi, z_f) \leq \bar{\pi}_j^I(\phi, z_f) \leq \bar{\pi}_j^I\left(\phi, \underline{z}_j(\alpha_f)\right) = \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot \underline{z}_j(\alpha_f)^{\sigma-1} \cdot \phi = W \cdot \alpha_f \cdot \phi.$$

This proves the first part of Proposition 2.

To prove the second part, consider the total profit for the inventor:

$$\Pi_j^I(\phi, z_f, \alpha_f) = \pi_j^I(\phi, z_f) - W \cdot \alpha_f \cdot \phi.$$

Note that conditional on $z_f > \underline{z}_j(\alpha_f)$, for all $\phi \in \left(0, \hat{\phi}_j(z_f)\right)$,

$$\begin{aligned}
\Pi_j^I(\phi, z_f, \alpha_f) &= \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot z_f^{\sigma-1} \cdot \phi - W \cdot \alpha_f \cdot \phi \\
&> \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot \underline{z}_j(\alpha_f)^{\sigma-1} \cdot \phi - W \cdot \alpha_f \cdot \phi = 0.
\end{aligned}$$

However, for sufficiently large ϕ,

$$\lim_{\phi\to+\infty} \Pi_j^I(\phi, z_f, \alpha_f) = \delta \cdot WF_j^M \cdot \left(\frac{z_f}{\tilde{z}_j}\right)^{\eta-1} - \lim_{\phi\to+\infty} W \cdot \alpha_f \cdot \phi < 0.$$

Therefore, by the Intermediate Value Theorem, there exists a quality cutoff $\bar{\phi}_j(z_f, \alpha_f)$ such that $\Pi_j^I\left(\bar{\phi}_j(z_f, \alpha_f), z_f, \alpha_f\right) = 0$. This cutoff is implicitly determined by

$$\delta \cdot WF_j^M \cdot \left(\frac{z_f}{\tilde{z}_j}\right)^{\eta-1} \cdot \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right) = W \cdot \alpha_f \cdot \bar{\phi}_j(z_f, \alpha_f),$$

which can be rearranged into

$$\begin{aligned}
\bar{\phi}_j(z_f, \alpha_f) &= \frac{\delta \cdot WF_j^M \cdot \left(\frac{z_f}{\tilde{z}_j}\right)^{\eta-1}}{W \cdot \alpha_f} \cdot \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right) \\
&= \frac{\delta \cdot WF_j^M \cdot z_f^{\eta-1}}{\underline{z}_j(\alpha_f)^{\sigma-1} \cdot \tilde{\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}} \cdot \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right) \\
&= \left(\frac{z_f}{\underline{z}_j(\alpha_f)}\right)^{\sigma-1} \cdot \frac{\delta \cdot WF_j^M \cdot z_f^{\eta-1}}{W^{1-\sigma} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}} \cdot \frac{1}{\tilde{\sigma}} \cdot \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right) \\
&= \left(\frac{z_f}{\underline{z}_j(\alpha_f)}\right)^{\sigma-1} \cdot \hat{\phi}_j(z_f) \cdot \frac{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma}}{\tilde{\sigma}} \cdot \kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right) \\
&= \left(\frac{z_f}{\underline{z}_j(\alpha_f)}\right)^{\sigma-1} \cdot \frac{\kappa_j\left(\bar{\phi}_j(z_f, \alpha_f), z_f\right)}{\kappa_{\min}} \cdot \hat{\phi}_j(z_f),
\end{aligned}$$

recalling that

$$\hat{\phi}_j(z_f) \equiv \frac{WF_j^M}{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma} \cdot W^{1-\sigma} P_j^{\sigma} X_j \cdot \tilde{z}_j^{\eta-1}} \cdot \delta \cdot z_f^{\eta-\sigma}.$$

This completes the proof.

B.5 Definition of Equilibrium

Definition A.1. *Given the fundamentals, including parameters on preference $\{\beta_j, \sigma, \eta\}$, wages and labor $\{W, L\}$, measure of inventors $\{N_j, N_j^*\}$, their distributions over labor productivity $\{G_{z,j}, G_{z,j}^*\}$, invention efficiency $\{G_{\alpha,j}, G_{\alpha,j}^*\}$, and product quality $\{G_{\phi,j}, G_{\phi,j}^*\}$, the fixed costs of imitation $\{F_j^M\}$ and the patent enforcement level δ, a competitive equilibrium of the model is characterized by a set of decision rules, prices, and allocations, such that $\forall j = 1, ..., J$, the following holds:*

1. *For all products invented, i.e. $\forall(\phi, z_f, \alpha)$ such that $e_j(\phi, z_f, \alpha) = 1$, the pricing decisions of inventors and imitators (if any) are optimal:*

$$p_j^I(\phi, z_f) = \mu_j^I(\phi, z_f) \cdot \frac{W}{z_f}, \quad \text{with } \mu_j^I(\phi, z_f) = \frac{\varepsilon_j^I(\phi, z_f)}{\varepsilon_j^I(\phi, z_f) - 1}. \tag{B.5}$$

$$\varepsilon_j^I(\phi, z_f) = \left(s_j^I(\phi, z_f) \cdot \sigma^{-1} + \left[1 - s_j^I(\phi, z_f)\right] \cdot \eta^{-1}\right)^{-1} \tag{B.6}$$

$$s_j^I(\phi, z_f) = \frac{p_j^I(\phi, z_f)^{1-\eta}}{p_j^I(\phi, z_f)^{1-\eta} + p_j^M(\phi, z_f)^{1-\eta}} \tag{B.7}$$

$$p_j^M(\phi, z_f) = M_j(\phi, z_f)^{\frac{1}{1-\eta}} \cdot \frac{\eta}{\eta - 1} \cdot \frac{W}{\tilde{z}_j}, \quad \text{where } \tilde{z}_j \equiv \left[\int_0^{+\infty} z_m^{\eta-1} \mathrm{d}G_{z,j}(z_m)\right]^{\frac{1}{\eta-1}} \tag{B.8}$$

2. *There is free entry for imitators, which implies that $M_j(\phi, z_f)$ is determined by*

$$p_j(\phi, z_f) \equiv \left[p_j^I(\phi, z_f)^{1-\eta} + p_j^M(\phi, z_f)^{1-\eta}\right]^{1-\eta} = \frac{\sigma}{\sigma - 1} \cdot \frac{W}{z_f} \cdot \min\left\{1, \quad \left[\frac{\hat{\phi}_j(z_f)}{\phi}\right]^{\frac{1}{\eta-\sigma}}\right\} \tag{B.9}$$

$$\hat{\phi}_j(z_f) \equiv \frac{\delta \cdot WF_j^M \cdot z_f^{\eta-\sigma}}{\tilde{\eta} \cdot [\sigma/(\sigma-1)]^{\eta-\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot \tilde{z}_j^{\eta-1}}, \quad \text{where } \tilde{\eta} \equiv (\eta - 1)^{\eta-1}/\eta^\eta \tag{B.10}$$

3. *Inventors' invention decisions for each product satisfy*

$$e_j(\phi, z_f, \alpha_f) = \mathbb{I}\left[\Pi_j^I(\phi, z_f, \alpha_f) > 0\right] \tag{B.11}$$

$$\Pi_j^I(\phi, z_f, \alpha_f) = \pi_j^I(\phi, z_f) - W \cdot \alpha_f \cdot \phi \tag{B.12}$$

$$\pi_j^I(\phi, z_f) = \begin{cases} \tilde{\sigma} \cdot W^{1-\sigma} P_j^\sigma X_j \cdot z_f^{\sigma-1} \cdot \phi & \text{if } \phi \leq \hat{\phi}_j(z_f) \\ \delta \cdot WF_j^M \cdot \left(\frac{z_f}{\tilde{z}_j}\right)^{\eta-1} \cdot \kappa_j(\phi, z_f) & \text{if } \phi > \hat{\phi}_j(z_f) \end{cases} \tag{B.13}$$

$$\text{where } \kappa_j(\phi, z_f) \equiv \tilde{\eta}^{-1} \cdot \left[\mu_j^I(\phi, z_f) - 1\right] \mu_j^I(\phi, z_f)^{-\eta} \tag{B.14}$$

4. *Firms' decisions are consistent with aggregate price indexes:*

$$P_j(z_f,\alpha_f)^{1-\sigma} = \int_0^{+\infty} e_j(\phi,z_f,\alpha_f)\cdot\phi\cdot p_j(\phi,z_f)^{1-\sigma}\,\mathrm{d}G_{\phi,j}(\phi) \tag{B.15}$$

$$P^*_j(z_f,\alpha_f)^{1-\sigma} = \int_0^{+\infty} e_j(\phi,z_f,\alpha_f)\cdot\phi\cdot p_j(\phi,z_f)^{1-\sigma}\,\mathrm{d}G^*_{\phi,j}(\phi) \tag{B.16}$$

$$\begin{aligned} P_j^{1-\sigma} &= N_j \int\int P_j(z_f,\alpha_f)^{1-\sigma}\mathrm{d}G_{z,j}(z_f)\mathrm{d}G_{\alpha,j}(\alpha_f) \\ &\quad + N^*_j \int\int P^*_j(z_f,\alpha_f)^{1-\sigma}\mathrm{d}G^*_{z,j}(z_f)\mathrm{d}G^*_{\alpha,j}(\alpha_f) \end{aligned} \tag{B.17}$$

5. *Total income equals total expenditures:*

$$P_jX_j = \beta_jE \tag{B.18}$$

$$E = WL + \sum_{j=1}^{J} N_j \int\int \Pi_j(z_f,\alpha_f)\mathrm{d}G_{z,j}(z_f)\mathrm{d}G_{\alpha,j}(\alpha_f) \tag{B.19}$$

$$\Pi_j(z_f,\alpha_f) = \int_0^{+\infty} e_j(\phi,z_f,\alpha_f)\cdot\Pi^I_j(\phi,z_f,\alpha_f)\,\mathrm{d}G_{\phi,j}(\phi) \tag{B.20}$$

Notice that ones income and prices $\{E, P_j\}$ are known, all other endogenous variables can be calculated sequentially, starting with the imitation block 2, and then the pricing and invention blocks 1 and 3. The equilibrium can then be viewed as a fixed point in $\{E, P_j\}$ such that the remaining blocks of equations 4 and 5 hold.

Appendix C Quantification

C.1 Model Fit

Table C.1 displays the details of the list of moments and the model fit.

C.2 Welfare Decomposition

In the model, aggregate real income is defined as E/P, where the nominal income

$$E = WL + \sum_j \Pi_j, \tag{C.1}$$

and aggregate price index

$$P = \prod_{j=0}^{J} \left(P_j/\beta_j\right)^{\beta_j}. \tag{C.2}$$

To decompose the log changes of aggregate variables into different industries, note that

$$\begin{aligned}
\mathrm{d}\ln E &= \frac{\sum_j \Pi_j}{WL + \sum_j \Pi_j} \times \mathrm{d}\ln\left(\sum_j \Pi_j\right) \\
&= \sum_j \frac{\sum_j \Pi_j}{WL + \sum_j \Pi_j} \times \frac{\Pi_j}{\sum_j \Pi_j} \times \mathrm{d}\ln \Pi_j, && \text{(C.3)} \\
\mathrm{d}\ln P &= \sum_j \beta_j \times \mathrm{d}\ln P_j. && \text{(C.4)}
\end{aligned}$$

To further decompose the changes in price indexes into contributions of firms from different countries, note that

$$\mathrm{d}\ln P_j = \frac{P_j^{Home\,1-\sigma}}{P_j^{Home\,1-\sigma} + P_j^{Foreign\,1-\sigma}} \times \mathrm{d}\ln P_j^{Home} + \frac{P_j^{Foreign\,1-\sigma}}{P_j^{Home\,1-\sigma} + P_j^{Foreign\,1-\sigma}} \times \mathrm{d}\ln P_j^{Foreign}, \tag{C.5}$$

where

$$\begin{aligned}
P_j^{Home\,1-\sigma} &= N_j \int\int P_j(z_f, \alpha_f)^{1-\sigma} \mathrm{d}G_{z,j}(z_f) \mathrm{d}G_{\alpha,j}(\alpha_f), && \text{(C.6)} \\
P_j^{Foreign\,1-\sigma} &= N_j^* \int\int P_j^*(z_f, \alpha_f)^{1-\sigma} \mathrm{d}G_{z,j}^*(z_f) \mathrm{d}G_{\alpha,j}^*(\alpha_f). && \text{(C.7)}
\end{aligned}$$

Thus, the derivation for welfare decomposition used in Table 4 and Figure 7 is complete.

Table C.1: Model Fit

	Metal Products and Machinery		Chemicals		Pharmaceuticals		Transport Equipment		Electrical Equipment		Electronics	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Industry Shares	0.11	-	0.09	-	0.02	-	0.09	-	0.06	-	0.14	-
Mean of MNE Global Patent Quality	1.92	-	2.40	-	2.04	-	1.87	-	1.93	-	2.07	-
Mean of Entered Home Patent Quality	1.68	1.44	2.09	1.70	1.36	1.16	1.47	1.36	1.51	1.58	1.54	1.54
Aggregate Market Share of Imitators	0.58	0.75	0.54	0.64	0.39	0.69	0.40	0.61	0.44	0.60	0.11	0.23
Aggregate Market Share of Home Inventors	0.07	0.04	0.21	0.21	0.35	0.17	0.15	0.20	0.17	0.12	0.08	0.01
Aggregate Market Share of Foreign Inventors	0.35	0.21	0.25	0.15	0.25	0.14	0.45	0.19	0.39	0.29	0.81	0.76
Mean of Logged Sales (Home)	0.86	0.70	0.97	1.00	0.50	0.41	1.51	1.07	1.15	0.83	0.57	0.23
Mean of Logged Sales (Foreign)	-0.04	-0.10	-0.15	-0.24	-0.26	-0.33	-0.11	-0.24	-0.07	-0.16	-0.03	-0.04
Std. Dev. of Logged Sales (Home)	1.62	1.36	1.83	1.41	1.59	1.62	2.23	1.14	1.69	1.24	2.00	1.21
Std. Dev. of Logged Sales (Foreign)	1.16	1.28	1.31	1.39	1.37	2.06	1.54	1.74	1.35	1.39	1.66	1.86
10th-p of Above-Med Patent Entry Rate (Home)	0.29	0.10	0.19	0.16	0.18	0.03	0.45	0.09	0.27	0.15	0.33	0.15
50th-p of Above-Med Patent Entry Rate (Home)	0.44	0.18	0.51	0.25	0.26	0.05	0.50	0.16	0.42	0.25	0.52	0.25
90th-p of Above-Med Patent Entry Rate (Home)	0.48	0.36	0.53	0.49	0.28	0.12	0.50	0.32	0.43	0.48	0.54	0.50
10th-p of Above-Med Patent Entry Rate (Foreign)	0.29	0.17	0.19	0.28	0.18	0.12	0.45	0.14	0.27	0.15	0.33	0.08
50th-p of Above-Med Patent Entry Rate (Foreign)	0.44	0.27	0.51	0.47	0.26	0.21	0.50	0.24	0.42	0.28	0.52	0.14
90th-p of Above-Med Patent Entry Rate (Foreign)	0.48	0.57	0.53	0.77	0.28	0.40	0.50	0.45	0.43	0.52	0.54	0.28

Notes: This table lists the targeted moments used for calibration and the model fit. The external moments are exactly matched to pin down $\{\beta_j, \theta_j^*\}$, and the internal moments are targeted to jointly calibrate the remaining parameters $\{\delta, \tau_{z,j}, \tau_{z,j}^*, \nu_{z,j}, \tau_{\alpha,j}, \tau_{\alpha,j}^*, \nu_{\alpha,j}, \theta_j, N_j^*\}$. The last column links moments to parameters that they best help identify. Logged sales are demeaned for all industries in both the data and the model.