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Distributional Gains from Innovation and Public Policy

By

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DISSERTATION

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DAVIS

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Contents

Distributional Gains from Innovation and Public Policy

Abstract

This dissertation consists of three chapters. The first chapter studies how the rise of China affects innovation in other countries. I emphasize the importance of *export competition*, which means the competition in third countries, in answering this question for three reasons. First, export competition with Chinese firms should be prevalent since Chinese exports have grown worldwide. Second, competition could be more intense in export markets due to the lack of home bias. Third, innovation is skewed toward high-productivity firms, many of which are exporters. To explore the export competition channel, I develop a multi-country model of innovation incorporating the quality preferences of consumers and the heterogeneous productivity of firms. The model predicts that more intense competition increases innovation of high-productivity firms, whereas it decreases innovation of low-productivity firms. The model also suggests that export competition could be more important than import competition in explaining innovation since high-productivity firms are exposed to export competition in more markets. These predictions are confirmed by the evidence from South Korean patent data using a novel firm-level measure of export competition developed in this chapter.

The second chapter studies whether regional development policy generates knowledge spillover effects. Causal inference on this question is not straightforward due to the endogenous location choice and the difficulty in measuring knowledge spillover. This chapter overcomes these challenges in four directions. First, a winner-loser comparison is conducted using a quasi-experimental South Korean Innovation City project, which relocates 112 public agencies with 41,364 employees from Seoul metropolitan area to provincial regions. Second, South Korean patent data are classified by the relevance with relocated public agencies to distinguish the direct effect of relocation and its spillover effect. Third, the patenting history of relocated agencies is used to measure the magnitude of shock precisely. Fourth, the physical distance and the traffic volume between municipalities are used to examine whether spillover effects are local. The empirical evidence shows that innovation increases in Innovation Cities both directly by the relocated agencies and by their co-work with local agencies. However, knowledge spillovers beyond Innovation Cities are limited to very close regions.

The third chapter, joint work with Robert Feenstra, explores a new mechanism through which the labor share in GDP falls in general equilibrium. We develop a general equilibrium model with non-CES preferences, occupational choice of ex-ante identical individuals, and the heterogeneous productivity of firms that explores the fiscal origin of the decline. The model suggests that (i) corporate-friendly fiscal policy decreases the labor share; and (ii) the labor share declines more when the entry of firms is restricted. This is because rigid entry adjustment prevents new entrants from entering the market, resulting in weaker competition between firms.

Chapter 1

Export Competition and Innovation

1.1 Introduction

As Chinese exports have grown exponentially after its accession to the World Trade Organization (WTO) in 2001, firms in other countries experience fierce competition with Chinese competitors not only in their domestic markets but also in their export markets. What are the consequences of rising competition with China in third countries (henceforth export competition)? Unlike the actively explored import competition with China (Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016; Autor et al., 2020a), little is known about the impact of export competition with Chinese firms. This chapter focuses on the innovation consequences of this under-explored export competition with China both theoretically and empirically since answering this question is crucial for at least three reasons. First, Chinese exports have increased worldwide in an unprecedentedly large magnitude, which suggests that export competition with Chinese firms should be prevalent.[1] Second, the impact of competition in export markets is expected to be substantial since a firm's product could be more substitutable in its export markets due to the lack of home bias.[2] Finally, since innovation is skewed toward a small number of high-productivity firms, many of which are exporters, export competition is expected to be important to innovating firms.[3] To my knowledge, this is the first attempt to study the innovation consequences of export competition with China.

[1]The Chinese share of manufacturing exports increased from 4.32% in 2001 to 10.32% in 2007. Imports from China increased in 200 out of 220 countries, growing 315% on average during the same period (*Source: Base pour l'Analyse du Commerce International (BACI)*).

[2]Indeed, Feenstra and Sasahara (2018) show that the elasticity of substitution between home and foreign goods is smaller than the elasticity of substitution between foreign goods.

[3]In the sample used in this study, exporters account for 78.5% of patent applications between 2001 and 2007 in South Korea.

From the perspective of theory, I develop a multi-country model with productivity-enhancing innovation incorporating quality preferences into a Melitz (2003) style heterogeneous firm model, where firms choose the quality of their products based on their productivity. The model shows that firms with higher productivity endogenously engage in more innovation because only high-productivity firms can afford the cost of innovation. More importantly, it is also shown that the rise of China, modeled as an exogenous increase in the number of Chinese entrants, increases the innovation of high-productivity firms and decreases that of low-productivity firms through the following mechanisms: *scale effect* and *export competition effect*.

To begin with the scale effect, as quality-adjusted prices fall due to the surging imports from China, the utility of consumers rises in importing countries. As a result of this utility increase, consumers regard product quality more importantly similar to Feenstra et al. (2014), which incentivizes firms to produce products with better quality. Therefore, the benefits of (productivity-enhancing) innovation increase since it costs more to produce higher-quality products. However, only high-productivity firms engage in more innovation since low-productivity firms cannot afford the cost of innovation facing the downward pressure on profits caused by more intense competition with China.

If only domestic market is considered, this scale effect is the only channel through which heterogeneous innovation responses arise in the model. However, since imports from China increase all over the world, exporting firms should be exposed to competition with China in foreign markets on top of the domestic market, each of which motivates exporting firms to innovate. By incorporating this extra innovation incentives arising from export competition explicitly, the model shows that high-productivity firms, who are likely to export to more markets, increase innovation more than low-productivity firms facing competition in multiple markets. As a result, this export competition effect strengthens the heterogeneous responses in innovation occurring from the scale effect further.

From the perspective of empirics, a novel firm-level measure of export competition is developed in this chapter considering all possible export markets where competition intensifies in line with the theoretical model. Then, the impact of export competition and import competition on innovation is examined with South Korean patent data matched to firm-level financial dataset KIS-VALUE since South Korea has several advantages in exploring this question. First, as a small open economy relying heavily on export markets,[4] competition in export markets is expected to have a sizable impact on South Koran firms. Second, the technology gap between South Korea and China is narrower than the gap between China and developed countries, which implies that the rise of China in export markets should be an effective pressure on Korean firms.[5] Third, South Korean firms actively engage in innovation, which enables a large-scale firm-level analysis.[6]

Empirical results are summarized as follows. First, the overall impact of export competition with China on South Korean innovation is positive, whereas that of import competition is not clear during the sample period 2001-2007. Second, only high productivity firms increase innovation in response to more intense competition with Chinese firms. While this tendency holds for both export competition and import competition, the impact is more consistent for export competition. Finally, it is shown that innovation is more responsive to export competition than to import competition, which is striking when the little attention that economists have paid to export competition is considered. These results are robust across alternative specifications, and an additional analysis using stronger export competition with East European countries that Korean firms experienced in European markets after the enlargement of the European Union (EU) supports the external validity of these findings.

The broadest strand of literature that this chapter fits into studies the relationship between competition and innovation, which is still inconclusive.[7] Theoretically, more intense competition can either decrease incentives to innovate by reducing potential rents from innovating (Schumpeter, 1942) or can motivate firms to increase innovation by reducing pre-innovation rents more than post-innovation rents (Arrow, 1962). Incorporating these two opposite views, Aghion et al. (2005) suggest that competition and innovation have an inverted-U shape relationship since competition changes the equilibrium composition of firms who are active and inactive in innovation.

Narrowing the scope, this chapter is closely related to the literature examining the innovation consequences of the China shock, which provides mixed evidence. For example, Autor et al. (2020a)

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[4] South Korea is the 14th largest exporting country between 2001 and 2007 (*source:* World Integrated Trade Solution) whose average exports to GDP ratio is as high as 34% during the same period (*source:* Bank of Korea).

[5] di Giovanni et al. (2014) estimate that South Korea is the tenth most technologically similar country to China. Among the top 10 countries, South Korea is the largest exporter.

[6] The number of total patent applications between 2001 and 2007 in South Korea is 969,093. Only Japan, the United States, and China lead South Korea during this period (*source:* World Intellectual Property Organization).

[7] For reviews on competition and innovation in general, see Gilbert (2006) and Cohen (2010). Shu and Steinwender (2019), Melitz and Redding (2021), and Akcigit and Melitz (2022) focus more on international trade and innovation.

show that firms in sectors with higher exposure to Chinese imports reduce R&D intensity and patent production in the United States. Li and Zhou (2017) also show that import competition with low-wage countries decreases the innovation of U.S. firms, whereas import competition with high-wage countries encourages innovation. However, Bloom et al. (2016) show that patents, IT intensity, TFP growth, and R&D expenditures increase in response to the rise of Chinese imports in European countries. Similarly, Medina (2017) show that Peruvian apparel manufacturers upgrade their product quality in response to the import competition with China. In contrast, Vancauteren et al. (2019) show that more intense import competition with China does not have a significant impact on patent applications of Dutch manufacturing firms. For South Korea, Ahn et al. (2018) show that patenting increases in response to Chinese import competition, and this tendency is more prominent for large firms and high-quality sectors. However, none of these investigate the intensifying competition with Chinese firms in foreign markets that this chapter emphasizes.

To my knowledge, the impact of competition with China in a third market has been analyzed solely in the context of Mexico and the United States. Specifically, how the increase in the U.S. imports from China affects Mexican labor market outcomes (Utar and Ruiz, 2013; Mendez, 2015; Robertson et al., 2020), firm activities (Iacovone et al., 2011, 2013), migration (Majlesi and Narciso, 2018), female bargaining power (Majlesi, 2016), and crimes (Dell et al., 2019) have been examined.[8] However, all of these investigate one export market, the United States. Instead, a firm-level measure of export competition developed in this chapter takes all export markets into account to capture export competition with China completely. Equipped with this measure, the differential impact of export competition and import competition on heterogeneous innovation responses of firms are examined both theoretically and empirically, which has not been explored thoroughly.

This study is also relevant to the literature that studies the heterogeneous innovation responses across firms. Equipped with firm-level data, it has been shown that more productive firms engage in more innovation, and the responses to shocks are heterogeneous across firms with different productivities. For instance, Bustos (2011) develops a heterogeneous firm model with innovation, which shows that only high-productivity firms adopt advanced technology due to the fixed cost of adoption when trade liberalizes. Bombardini et al. (2017) also show that the impact of import

[8] Among these, Iacovone et al. (2011) use an outcome variable most closely related to innovation, which is the introduction of new managerial strategies. However, this is not directly related to the new invention, which is an engine of growth.

competition is heterogeneous across firms in that only those close to the technology frontier increase innovation. The model's prediction of heterogeneity is empirically supported using Chinese data. Considering the growth in the size of export market as a shock, Aghion et al. (2018) argue that high-productivity firms innovate more than low-productivity firms as a result of the rising competition between producers, which decreases the marginal benefit of innovation disproportionately for low-productivity firms. French data confirm this prediction of heterogeneous innovation. The current chapter complements this line of research both theoretically and empirically by exploring a different channel and different environments.

The contributions of this study to the literature are threefold. First, a model developed in this study suggests not only import competition but also export competition matters in firms' innovation decisions. The model also emphasizes the role of product quality, which has become an important area of research, and the existence of multiple export markets in explaining why heterogeneous response arises. Shedding light on new mechanisms, the model provides a conceptual framework to understand what export competition is and how export competition affects innovation, which is new to the literature. Second, by confirming the importance of export competition and the heterogeneous responses empirically, this study provides a new perspective to explore the China syndrome. Even though economists have expanded our understandings beyond the import competition with China by studying offshoring to China (Mion and Zhu, 2013), input-output linkages related to Chinese intermediate inputs (Caliendo et al., 2019; Aghion et al., 2021), and exports to China (Feenstra et al., 2019), we are still lack of research on the competition with Chinese firms in third markets. A novel firm-level measure of export competition developed in this study is expected to be useful in answering this question since the difficulty in measuring the intensity of export competition with China has been one of the barriers that leave its impact under-explored despite its potential importance. Third, by examining one of the newly industrialized countries, South Korea, this study adds to the debate on whether and how competition affects innovation in different environments.

The remaining part of the chapter proceeds as follows. In Section 1.2, a baseline theoretical model is developed. In Section 1.3, the impact of competition on innovation is analyzed. In Section 1.4, data are described, and the measure of export competition is introduced. In Section 1.5, empirical strategies and estimation results are reported. Section 1.6 concludes.

1.1.1 Consumer Problem

The utility function of a representative consumer in country s is:

$$U_s = \rho_s^0 ln q_s^0 + \rho_s^1 ln Q_s \quad \text{where } \rho_s^0 + \rho_s^1 = 1\,,\ \ \rho_s^0, \rho_s^1 \geq 0 \tag{1.1}$$

where q_s^0 is the consumption of the homogeneous good. Q_s is a Dixit-Stiglitz aggregator over consumption bundles Q_{ks}, sourced from country k, each of which combines differentiated goods incorporating quality preferences:[9]

$$Q_s = \left(\sum_k Q_{ks}^{\frac{\sigma_s-1}{\sigma_s}}\right)^{\frac{\sigma_s}{\sigma_s-1}}, \quad \text{where } Q_{ks} = \left[\int_{\omega\in\Omega_{ks}} \left(z_{ks}(\omega)^{\delta_s} q_{ks}(\omega)\right)^{\frac{\sigma_s-1}{\sigma_s}} d\omega\right]^{\frac{\sigma_s}{\sigma_s-1}} \text{ and } \sigma_s > 1 \tag{1.2}$$

where subscript k and s indicate the source country and the destination country, respectively. Using these country subscripts, $z_{ks}(\omega)$ means an index of the quality of variety ω that is imported from k to s, and δ_s indicates the intensity of quality preferences in s. δ_s is assumed to be positive so that consumers value product quality.[10] σ_s is the elasticity of substitution between products in s, and Ω_{ks} is the set of varieties that s imports from k.[11] Noting that the consumer spends ρ_s^1 fraction of her normalized income on differentiated products as implied by the Cobb-Douglas utility function (1.1), the demand function (per consumer) for variety ω can be derived as

$$q_{ks}(\omega) = p_{ks}(\omega)^{-\sigma_s} z_{ks}(\omega)^{\delta_s(\sigma_s-1)} \rho_s^1 P_s^{\sigma_s-1}, \tag{1.3}$$

where $p_{ks}(\omega)$ is the price of variety ω. The quality adjusted price index of differentiated products in country s, P_s, is defined as the aggregate of P_{ks}, which is the price index of imports from k:

$$P_s = \left(\sum_k P_{ks}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}, \text{ where } P_{ks} = \left[\int_{\omega\in\Omega_{ks}} z_{ks}(\omega)^{\delta_s(\sigma_s-1)} p_{ks}(\omega)^{\,1-\sigma_s} d\omega\right]^{\frac{1}{1-\sigma_s}}. \tag{1.4}$$

[9] Quality preferences are introduced in various ways. Some examples include Hallak (2006), Verhoogen (2008), Hallak and Schott (2011), Hallak and Sivadasan (2013), Feenstra et al. (2014), Antoniades (2015), Aw and Lee (2017). (1.2) is identical to that of Hallak and Sivadasan (2013) except that the source country k is explicitly introduced.

[10] When $\delta_s = 0$, consumers have the traditional CES preferences.

[11] Source country k includes the destination country s itself.

Intuitively, demand is decreasing in price and increasing in quality. Since there are L_s identical consumers in each market s, the quantity demanded for a firm from country k selling ω in market s is $L_s q_{ks}(\omega)$.

1.1.2 Firm Problem

Following Feenstra et al. (2014), firms may choose different product quality for each destination. Both marginal costs and fixed costs are increasing in the quality of product similar to Hallak and Sivadasan (2013). Noting that each firm is characterized by its productivity ϕ, the marginal costs of country k's firm with productivity ϕ targeting market s are

$$c_{ks}(\phi) = \frac{z_{ks}(\phi)}{\phi}, \tag{1.5}$$

which shows that it costs more to produce a good with higher quality. At the same time, (1.5) reflects that a firm with higher ϕ can produce the same product at lower marginal costs. In addition, to sell in market s, the firm has to pay fixed costs

$$F_{ks}(\phi) = F_{ks} + f_{ks} z_{ks}(\phi)^{\alpha} \quad \text{where } \alpha > 0, \tag{1.6}$$

where F_{ks} is a part of fixed costs that does not depend on quality, and f_{ks} is a part of fixed costs that interacts with quality.[12] Fixed costs are destination-specific, and the quality-elasticity of fixed costs α is assumed to be positive.[13] Therefore, fixed costs are higher for firms producing higher quality products and may vary across destinations.

Note that this cost structure reveals that a firm's choice in one market does not affect its choice in other markets. Therefore, a firm chooses which markets to serve and maximizes its profits in each destination independently. More specifically, a firm with ϕ chooses the price and the quality of its product for market s considering the demand function (1.3) to maximize its profits earned in market s. Since the behavior of firms of the same origin is of interest, the firm problem can be

[12] Quality-dependent fixed costs may include both tangible and intangible components. For instance, maintaining high-quality equipment, training workers, and paying a licensing fee for using advanced technology to produce high-quality products increase fixed costs.

[13] The quality-elasticity of fixed costs can be origin-specific α_k. However, a simpler notation α is used since it does not alter the conclusion.

written as follows omitting the origin subscript k for the simplicity of notation:

$$\underset{p_s(\phi),z_s(\phi)}{Max}\Big\{(p_s(\phi)-c_s(\phi))L_s p_s(\phi)^{-\sigma_s} z_s(\phi)^{\delta_s(\sigma_s-1)}\rho_s^1 P_s^{\sigma_s-1}-F_s(\phi)\Big\}. \tag{1.7}$$

Noting that standard optimization yields $p_s(\phi)=\frac{\sigma_s}{\sigma_s-1}c_s(\phi)=\frac{\sigma_s}{\sigma_s-1}\frac{z_s(\phi)}{\phi}$, the maximization problem reduces to choosing just $z_s(\phi)$

$$\underset{z_s(\phi)}{Max}\left\{\frac{L_s}{\sigma_s}\Big(\frac{\sigma_s}{\sigma_s-1}\frac{z_s(\phi)}{\phi}\Big)^{1-\sigma_s} z_s(\phi)^{\,\delta_s(\sigma_s-1)} P_s^{\sigma_s-1}-F_s-f_s z_s(\phi)^{\alpha}\right\}. \tag{1.8}$$

Using the first order condition, the optimal quality choice of a firm with ϕ is derived as

$$z_s(\phi)=\Big[\frac{L_s(\delta_s-1)}{\alpha f_s}\Big(\frac{\sigma_s-1}{\sigma_s}\Big)^{\sigma_s}\phi^{\sigma_s-1}\rho_s^1 P_s^{\sigma_s-1}\Big]^{\frac{1}{\beta_s}}\ , \quad \text{where}\ \ \beta_s\equiv\alpha-(\delta_s-1)(\sigma_s-1) \tag{1.9}$$

where $\delta_s>1$ and $\beta_s>0$ are assumed to guarantee that $z_s(\phi)$ is increasing in ϕ and decreasing in f_s. This assumption means that the intensity of quality preference δ_s is larger than one, but not too large to dominate the quality-elasticity of fixed cost α. Then, using (1.8) and (1.9), it can be shown that the profits a firm with ϕ earns from market s are

$$\pi_s(\phi)=\Big[\Big(\frac{\rho_s^1 L_s(\delta_s-1)}{\alpha f_s}\Big)\Big(\frac{\sigma_s-1}{\sigma_s}\Big)^{\sigma_s}\Big]^{\frac{\alpha}{\beta_s}}\frac{\beta_s f_s}{\alpha-\beta_s}\phi^{\xi_s}P_s^{\xi_s}-F_s\ , \quad \text{where}\ \xi_s\equiv\frac{\alpha(\sigma_s-1)}{\beta_s}. \tag{1.10}$$

Note that ξ_s is always positive since $\beta_s>0$ and $\sigma_s>1$ are already assumed. Note further that ξ_s is a combination of parameters from consumer preferences (σ_s and δ_s) and production technology (α). Since this is a key parameter for comparative statics, it will be discussed further in Section 3. Intuitively, profits earned from each market s is increasing in the effective market size $\rho_s^1 L_s$ and productivity ϕ. Summing up the profits from all markets, the total profits of a firm with ϕ becomes

$$\Pi(\phi)=\sum_s \pi_s(\phi) \tag{1.11}$$

1.1.3 Equilibrium

(1) Zero profit cutoff

The zero profit cutoff productivity ϕ_s is defined for each destination s as the level of ϕ such that

$\pi_s(\phi) = 0$. Since $\pi_s(\phi)$ is increasing in ϕ, firms with $\phi > \phi_s$ make positive profits selling to market s. Using (1.10), ϕ_s is derived as

$$\phi_s = \left\{ \frac{F_s}{\left[\left(\frac{\rho_s^1 L_s(\delta_s - 1)}{\alpha f_s}\right)\left(\frac{\sigma_s - 1}{\sigma_s}\right)^{\sigma_s}\right]^{\frac{\alpha}{\beta_s}} \frac{\beta_s f_s}{\alpha - \beta_s} P_s^{\xi_s}} \right\}^{\frac{1}{\xi_s}}. \tag{1.12}$$

Since there are S countries, each country has S cutoff productivities, and there are S^2 cutoff productivities in the model. However, (1.12) shows that P_s is the only endogenous variable that determines ϕ_s. To be more precise with notation, the cutoff productivities for country k's firms to sell in market s (i.e. ϕ_{ks}) are automatically determined as a function of P_s and exogenous parameters for all $k = 1, 2, .., S$. This suggests that the equilibrium can be found with S more equations, which are established by the free entry condition.

(2) Free entry condition

The free entry condition requires the expected profits to be the same as the fixed entry cost F_e in equilibrium. Noting that (1.10) can be written as $\pi_s(\phi) = \left[\left(\frac{\phi}{\phi_s}\right)^{\xi_s} - 1\right]F_s$ using (1.12), the free entry condition becomes

$$\sum_s \int_{\phi_s}^{\infty} \left[\left(\frac{\phi}{\phi_s}\right)^{\xi_s} - 1\right] F_s dG(\phi) = F_e, \tag{1.13}$$

where the left-hand side indicates the expected profits. Since the free entry condition is defined for each country, there are S different free entry conditions. Combining these with S unknowns from (1.12), all ϕ_s can be pinned down.

(3) Firm-level performance measures

Using the cutoff productivity ϕ_s, firm-level performance measures in market s can be written as

$$z_s(\phi) = \left[\frac{F_s(\alpha - \beta_s)}{\beta_s f_s}\left(\frac{\phi}{\phi_s}\right)^{\xi_s}\right]^{\frac{1}{\alpha}} \tag{1.14}$$

$$p_s(\phi) = \frac{\sigma_s}{(\sigma_s - 1)\phi}\left[\frac{F_s(\alpha - \beta_s)}{\beta_s f_s}\left(\frac{\phi}{\phi_s}\right)^{\xi_s}\right]^{\frac{1}{\alpha}} \tag{1.15}$$

$$q_s(\phi) = \frac{\alpha f_s \phi}{L_s(\delta_s - 1)}\left[\frac{F_s(\alpha - \beta_s)}{\beta_s f_s}\left(\frac{\phi}{\phi_s}\right)^{\xi_s}\right]^{\frac{\alpha-1}{\alpha}} \tag{1.16}$$

$$r_s(\phi) = \frac{\sigma_s \alpha F_s}{\beta_s}\left(\frac{\phi}{\phi_s}\right)^{\xi_s} \tag{1.17}$$

$$F_s(\phi) = \left[1 + \frac{\alpha - \beta_s}{\beta_s}\left(\frac{\phi}{\phi_s}\right)^{\xi_s}\right] F_s \tag{1.18}$$

$$\pi_s(\phi) = \left[\left(\frac{\phi}{\phi_s}\right)^{\xi_s} - 1\right] F_s, \tag{1.19}$$

all of which depend on $\frac{\phi}{\phi_s}$. Four things are noteworthy. First, the price a firm charges in each market may increase or decrease in productivity depending on the parameter. More specifically, the price increases in ϕ when $\alpha < \delta_s(\sigma_s - 1)$. However, in the absence of quality preferences, heterogeneous firm models always predict a negative relationship between price and productivity. Interestingly, empirical results in the literature suggest mixed evidence (see Crozet et al. (2012) and Antoniades (2015) for relevant discussion). Second, the quantity a firm sells in each market can decrease in ϕ when $\alpha < \frac{\delta_s(\sigma_s - 1)}{\sigma_s}$. For instance, when product quality is very important, the most productive firm may sell only a small quantity of high quality product.[14] Third, the fixed costs of a firm increases in productivity ϕ since firms with higher productivity produce higher quality products. In real world, quality-related fixed costs are required for trade marks, licenses, worker training, intangible assets, or advertisement, which are gaining more importance. Therefore, the role of increasing fixed cost should be more seriously considered. However, this feature is not emphasized in models without quality preferences.[15] Fourth, product quality, revenues, and profits of a firm are increasing in productivity ϕ, which is intuitive.

[14] This is not rare for luxury brands.

[15] Melitz (2003) style heterogeneous firm models with CES preferences assume a constant fixed cost of production. Heterogeneous firm models with preferences satisfying Marshall's second law of demand usually assume no fixed cost due to the computation complexity (Melitz and Ottaviano, 2008; Feenstra, 2018a; Aghion et al., 2018; Autor et al., 2020b).

(4) Income-spending condition

Finally, the mass of entrants and the number of available varieties in each market are determined by the income-spending condition, which implies that the total income of a country is the same as the total spending of the country on domestic and imported products. Formally, it can be written as

$$L_s = \rho_s^0 L_s + \sum_k M_k \int_{\phi_{ks}}^{\infty} r_{ks}(\phi) dG(\phi), \tag{1.20}$$

where the left-hand side stands for the total income of country s, whereas the right-hand side indicates the total spending. First, since each consumer spends ρ_s^0 fraction of her income on the homogeneous good, $\rho_s^0 L_s$ is spent on the homogeneous sector. Second, among M_k firms entering the differentiated sector from country k, only firms with productivity higher than ϕ_{ks} sell their products in market s earning revenues $r_{ks}(\phi)$. Since the zero profit condition and the free entry condition determine ϕ_{ks} and $r_{ks}(\phi)$, (1.20) implies that there are S equations and S unknowns. Therefore, the mass of entrants M_k in each country can be derived. Then, since $1 - G(\phi_{ks})$ fraction of M_k entrants in country k can sell to market s, the number of varieties available in market s can be derived as

$$V_s = \sum_k M_k (1 - G(\phi_{ks})) \tag{1.21}$$

1.1.4 Innovation Decision

Now, assume that productivity-enhancing innovation is available. Assume further that innovation cost is quadratic in the probability of successful innovation as in Bombardini et al. (2017). More specifically, when a firm invests $C(I) = \frac{1}{2\nu} I^2$, its productivity ϕ increases to $\gamma\phi$, where $\gamma > 1$, with a probability of I. Since productivity improvement applies to all products regardless of the destination, a firm with ϕ determines the level of $I(\phi)$, which is equivalent to choosing the level of innovation investment, by solving

$$\underset{I(\phi)\in[0,1]}{Max} \left\{ \Pi(\phi) + I(\phi)\big(\Pi(\gamma\phi) - \Pi(\phi)\big) - \frac{1}{2\nu} I(\phi)^2 \right\}, \tag{1.22}$$

which reflects pre-innovation profits, the probability of success, the profit increase following successful innovation, and the cost of innovation investment. The first order condition yields

$$I(\phi) = \left[\sum_s \left(\pi_s(\gamma\phi) - \pi_s(\phi)\right)\right] \times \nu. \tag{1.23}$$

Therefore, the optimal level of innovation investment of a firm with ϕ becomes

$$I(\phi) = min\left\{1\,,\, \sum_s \left[\mathbf{1}(\phi < \phi_s < \gamma\phi)\big[\big(\frac{\gamma\phi}{\phi_s}\big)^{\xi_s} - 1\big]F_s\nu + \mathbf{1}(\phi > \phi_s)(\gamma^{\xi_s} - 1)\left(\frac{\phi}{\phi_s}\right)^{\xi_s} F_s\nu\right]\right\} \tag{1.24}$$

where $\mathbf{1}(\phi < \phi_s < \gamma\phi) = 1$ when $\phi < \phi_s < \gamma\phi$, and $\mathbf{1}(\phi > \phi_s) = 1$ when $\phi > \phi_s$. Note that firms with $\phi < \phi_s < \gamma\phi$ sell to new market s only if innovation succeeds. For simplicity, suppose that firms do not take into account this possibility.[16] Then, (1.24) simplifies to

$$I(\phi) = min\left\{1\,,\, \sum_s I_s(\phi)\right\} \quad \text{where } \; I_s(\phi) = \mathbf{1}(\phi > \phi_s)(\gamma^{\xi_s} - 1)\left(\frac{\phi}{\phi_s}\right)^{\xi_s} F_s\nu. \tag{1.25}$$

$I(\phi)$ is increasing in ϕ for two reasons. First, at the intensive margin, each $I_s(\phi)$ is increasing in ϕ since ξ_s is assumed to be positive. Second, at the extensive margin, since firms with larger ϕ export to more destinations, more $I_s(\phi)$ with positive values are added. Importantly, this extensive margin does not exist in the closed economy, and is limited when there are only two countries in the world. For more interesting cases, γ and ν are assumed to be in a range such that a threshold productivity above which all firms engage in $I(\phi) = 1$ is very high. By doing so, I focus on the range of ϕ where $I(\phi) < 1$, which simplifies (1.25) further to

$$I(\phi) = \sum_s I_s(\phi) \quad \text{where } \; I_s(\phi) = \mathbf{1}(\phi > \phi_s)(\gamma^{\xi_s} - 1)\left(\frac{\phi}{\phi_s}\right)^{\xi_s} F_s\nu. \tag{1.26}$$

1.2 Competition and Innovation

In this section, the impact of rising competition with Chinese firms on innovation is examined. To do so, the quality intensity parameter δ_s is assumed to be increasing in the level of utility similar

[16] For instance, γ can be assumed to be close to one. Then, $\big[\big(\frac{\gamma\phi}{\phi_s}\big)^{\xi_s} - 1\big]F_s\nu$ will be small and the range of firms with $\phi < \phi_s < \gamma\phi$ should be narrow. Therefore, ignoring $\mathbf{1}(\phi < \phi_s < \gamma\phi)\big[\big(\frac{\gamma\phi}{\phi_s}\big)^{\xi_s} - 1\big]F_s\nu$ would not be problematic. This assumption is for the mathematical convenience, and the main results do not change without this assumption.

to Feenstra et al. (2014).[17] More formally, the intensity of quality preferences in country s is

$$\delta_s(U_s) = \delta_s^0 + h_s(U_s)\ , \ \text{ where } \ h_s'(U_s) > 0, \tag{1.27}$$

where δ_s^0 is constant, whereas $h_s(U_s)$ is increasing in U_s. Then, the utility function (1.1) implicitly defines the representative consumer's utility. However, since $h_s(U_s)$ is assumed to be monotonically increasing in U_s, and since $\delta_s(U_s)$ will be a constant value in equilibrium, (1.1) can be regarded as a direct utility function in solving consumer problem.[18] Therefore, every step taken in Section 1.2 holds except that δ_s and ξ_s should be understood as $\delta_s(U_s)$ and $\xi_s(U_s)$, respectively.

Now, the rise of competition with China is introduced as an exogenous increase in the number Chinese firms following the structural reforms in China. More specifically, it is assumed that the entry of firms in China increases since structural changes related to the accession to the WTO increases the expected profits in China. For instance, since the United States Congress granted the Permanent Normal Trade Relations (PNTR) status as China joined the WTO, the risk of tariff increase following the revocation of Chinese Most Favored Nation (MFN) status disappeared (Handley and Limão, 2017). In consequence, the expected profits and the entry of firms in China could have increased.[19] Its impact on market s served by Chinese firms can be summarized as the following proposition.

Proposition 1. In market s served by Chinese firms, the rise of China leads to:

(1) an increase in the cutoff productivity to sell in market s,

(2) an increase in ξ_s.

[17] This assumption reflects empirical evidence on the positive relationship between quality preferences and income (Hallak, 2006; Verhoogen, 2008; Bastos et al., 2018).

[18] It is similar to the *guess and verify* approach in macroeconomics. Suppose that the consumer guesses her equilibrium utility and takes δ_s corresponding to the guess in maximizing her utility. If the solved utility is not the same as her initial guess, she updates her belief and solves the problem again until the her guess is correct. In the end, when the guess is correct, (1.1) can be regarded as a direct utility function.

[19] Amiti et al. (2020) show that growth of Chinese exports after its accession to the WTO is mostly driven by new firms entering export markets. Alternatively, it can be assumed that the productivity of incumbent Chinese firms increases, which leads to the same conclusion as shown in Appendix A.1.

Proof. The price index of differentiated products in market s or (1.4) can be rewritten as

$$P_s = \left(P_{cn,s}^{1-\sigma_s} + \sum_{k \neq cn} P_{ks}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}, \text{ where } P_{cn,s} = \left(M_{cn} \int_{\phi_{cn,s}}^{\infty} z_{cn,s}(\phi)^{\delta_s(\sigma_s - 1)} p_{cn,s}(\phi)^{1-\sigma_s} dG(\phi) \right)^{\frac{1}{1-\sigma_s}} \tag{1.28}$$

by separating the price index of imports from China $P_{cn,s}$ out. Then, an exogenous increase in the number of Chinese firms M_{cn} drives the Chinese component of price index $P_{cn,s}$, and therefore P_s, downward. This fall in P_s directly decreases the profits of firms selling in market s as is clear from (1.10). Therefore, the cutoff productivity for selling in market s increases.

In addition, the fall in P_s has an indirect effect. Using the corresponding demand function, it can be shown that consumer's utility can be expressed as

$$U_s = \rho_s^0 ln q_s^0 + \rho_s^1 ln \rho_s^1 P_s^{-1}, \tag{1.29}$$

which is decreasing in the price index. This implies that the rise of China increases consumer's utility in country s. As a result of this utility increase, $\delta_s(U_s)$ and $\xi_s(U_s)$ become larger.[20] $\square$

Not surprisingly, the rise of Chinese firms leads to the decrease in prices in importing countries[21] and imposes the downward pressure on profits of competing firms as is evident from (1.19). More interestingly, (1.19) shows that profits become more sensitive to productivity as ξ_s increases. As a result of the rise of Chinese firms, consumers in market s feel wealthier, and they consider quality more importantly. Therefore, the ability to produce high quality product becomes more important, and profits become more sensitive to productivity.

Now, to examine the innovation consequence of the rise of China, note that the innovation investment $I(\phi)$ can be decomposed into each market component $I_s(\phi)$ as in (1.26). This implies that the impact of more intense competition on innovation can be also decomposed into contributions from each market. Denoting the new level of $I(\phi)$ and $I_s(\phi)$ as $I^{new}(\phi)$ and $I_s^{new}(\phi)$, the

[20]In general equilibrium, the rise of China leads to the entry adjustment, which changes the number of entrants, cutoff productivities, and prices for all countries. However, as long as P_s decreases as $P_{cn,s}$ falls, the conclusion is not affected.

[21]Indeed, Auer and Fischer (2010) show that imports from low-wage countries impose strong downward pressure on prices in the United States.

innovation response to the rise of Chinese competitors is decomposed as

$$I^{new}(\phi) - I(\phi) = \sum_s \big(I_s^{new}(\phi) - I_s(\phi)\big). \tag{1.30}$$

Given this decomposition, Proposition 2 summarizes how each market component $I_s(\phi)$ responds to more intense competition in market s.

Proposition 2. An increase in competition in market s decreases $I_s(\phi)$ of low productivity firms and increases $I_s(\phi)$ of high productivity firms.

Proof. As shown in Proposition 1, more intense competition in market s increases ϕ_s and ξ_s. Denoting this higher level of ϕ_s and ξ_s as ϕ_s^{new} and ξ_s^{new}, the innovation response can be written as

$$I_s^{new}(\phi) - I_s(\phi) = \begin{cases} 0\,, \quad \text{when } \phi \le \phi_s \\ -(\gamma^{\xi_s} - 1)\left(\frac{\phi}{\phi_s}\right)^{\xi_s} F_s \nu\,, \quad \text{when } \phi_s < \phi \le \phi_s^{new} \\ F_s\nu\big[(\gamma^{\xi_s^{new}} - 1)\big(\frac{\phi}{\phi_s^{new}}\big)^{\xi_s^{new}} - (\gamma^{\xi_s} - 1)\big(\frac{\phi}{\phi_s}\big)^{\xi_s}\big]\,, \quad \text{when } \phi > \phi_s^{new}. \end{cases} \tag{1.31}$$

First, firms with $\phi \le \phi_s$ do not sell in market s even before competition intensifies. So, tougher competition in market s does not affect the innovation response of those firms. Second, the least productive firms selling in market s with productivity $\phi_s < \phi \le \phi_s^{new}$ exit market s and decrease innovation as ϕ_s increases following Proposition 1. Third, the response of surviving firms in market s with $\phi > \phi_s^{new}$ is heterogeneous across firms. To see this, note that innovation increases if and only if $(\gamma^{\xi_s^{new}} - 1)\big(\frac{\phi}{\phi_s^{new}}\big)^{\xi_s^{new}} > (\gamma^{\xi_s} - 1)\big(\frac{\phi}{\phi_s}\big)^{\xi_s}$, which is equivalent to

$$\frac{\gamma^{\xi_s^{new}} - 1}{\gamma^{\xi_s} - 1} \times \big(\frac{\phi}{\phi_s}\big)^{\xi_s^{new} - \xi_s} \times \big(\frac{\phi_s}{\phi_s^{new}}\big)^{\xi_s^{new}} > 1. \tag{1.32}$$

The first component of (1.32) implies that innovation increases since $\xi_s^{new} > \xi_s$ and $\gamma > 1$. In contrast, the third component indicates that innovation decreases since $\phi_s < \phi_s^{new}$. However, the second component shows that the innovation response is heterogeneous in that it increases in ϕ without bound. Therefore, considering these countervailing forces, for any given change in ϕ_s and

ξ_s, there exists a threshold T_s such that innovation increases for all $\phi > T_s$. In consequence, $I_s(\phi)$ increases for firms with sufficiently high productivity.[22] $\square$

This proposition shows that $I_s^{new}(\phi) - I_s(\phi)$ is generally increasing in ϕ for all s.[23] The underlying mechanism is as follows. As competition escalates, firms want to differentiate their products by producing higher-quality products. As a result, the benefits of productivity-enhancing innovation become larger since innovation makes it cheaper to produce higher-quality products. However, only high-productivity firms engage in more innovation due to the fixed cost of innovation and the downward pressure on profits. This *scale effect* increases the innovation gap between high-productivity and low-productivity firms as competition intensifies.

Finally, by aggregating the change in each market component $I_s(\phi)$, the innovation response of firms to the rise of China is determined. The following proposition summarizes the heterogeneous innovation responses of firms considering both import competition and export competition.

Proposition 3. High-productivity firms increase innovation, whereas low-productivity firms decrease innovation in response to competition with China.

Proof. The innovation response decomposition (1.30) can be rewritten by separating the domestic market and export markets explicitly as follows:

$$I^{new}(\phi) - I(\phi) = \underbrace{I_{home}^{new}(\phi) - I_{home}(\phi)}_{contributions\ from\ import\ competition} + \underbrace{\sum_{s \neq home} \left(I_s^{new}(\phi) - I_s(\phi)\right)}_{contributions\ from\ export\ competition} . \tag{1.33}$$

Since Proposition 2 applies to all $I_s^{new}(\phi) - I_s(\phi)$ in (1.33), each market component increases for high-productivity firms and decreases for low-productivity firms due to the scale effect at the intensive margin. When only import competition in the domestic market is considered, this is the only effect that explains how firms change innovation. However, when export competition in third

[22] Indeed, this innovation response is not limited to firms in country k. Since all firms competing in market s are affected by export competition with China, high productivity firms originated from other countries also engage in more innovation. As shown in Appendix A.1, this productivity improvement decreases the price index P_s further, which strengthens Proposition 1 and therefore Proposition 2.

[23] It is decreasing when productivity is relatively low ($\phi \in [\phi_s, \phi_s^{new}]$).

markets is considered, high-productivity firms increase innovation further at the extensive margin because the innovation incentives accumulate over destination countries. In other words, since high-productivity exporting firms face tougher competition in more markets, they engage in more innovation to escape from multi-layered competition. Due to this *export competition effect* and the scale effect, high-productivity firms increase innovation, whereas low-productivity firms decrease innovation in response to both import competition and export competition with China. □

Even though the model is clear about the innovation response increasing in productivity facing tougher competition with China, there remain two questions unanswered by the model. First, since low- productivity firms decrease innovation, whereas high-productivity firms increase innovation, the overall impact of competition on innovation is ambiguous. This is true for both import competition and export competition.

A more interesting question is the relative importance of import competition and export competition in firm's innovation. In reality, firms may respond more actively to export competition than to import competition for many reasons. For instance, the size of export market could be larger than domestic market, which makes firms more responsive to export competition. In addition, since Korean products and Chinese products are expected to be more substitutable in third countries due to the lack of home bias, the effective pressure of the rise of Chinese firms on Korean firms is likely to be stronger in export markets. In other words, since the elasticity of substitution between Korean products and Chinese products is smaller in Korea than in the United States, Korean manufacturers may perceive competition with Chinese competitors tougher in the United States than in Korea. Furthermore, when consumers in third countries consider quality more importantly than domestic consumers, the incentive to innovate to differentiate quality could be stronger when competition in export markets intensifies. The innovation decomposition (1.33) suggests this possibility. However, without making parametric assumptions, it is not clear whether innovation is more responsive to export competition or import competition. Answering this requires an empirical examination.

1.3 Data

1.3.1 Data Sources, Matching, and Sample Restrictions

Trade data are sourced from CEPII's BACI, which provides bilateral trade data by 6-digit Harmonized System (HS) classification for more than 5000 products. Since trade flows are reported by both exporters and importers, the inconsistency between exports and imports information is not unusual in the UN Comtrade database. BACI provides a single figure of bilateral trade flow reconciling the inconsistency in trade flows. It also provides more consistent unit value data than the raw data (Gaulier and Zignago, 2010). To link 6-digit HS code with Korean Standard Industry Classification (KSIC), both classifications are converted to 4-digit International Standard Industry Classification (ISIC) code using the World Integrated Trade Solution concordance table and the concordance table provided by Statistics Korea.

The universe of South Korean patent data from 1948 is available from Korea Intellectual Property Rights Information Service (KIPRIS). Each patent has a unique application number, the date of application, the name and the address of applicants with identifiers, the name and the address of inventors, International Patent Classification (IPC) codes, and citation information among others.[24] Figure 1.1 shows an example of the information of a patent that can be searched on the KIPRIS. This invention is related to IPCs like C11D 3/43, C11D 3/20, and H01L 21/304, and was co-applied for a patent on November 18th, 2014 by Samsung SDI and Samsung Electronics. A unique application number 10-2014-0161215 is assigned to this application and four prior patents are cited.

This dataset is matched to a firm-level dataset KIS-VALUE, which is created and managed by the largest credit rating agency in South Korea, NICE Korean Information Service. The dataset includes all firms that are required to be audited.[25] Administrative corporation registration numbers and business registration numbers are used to match KIS-VALUE to patent data as follows. First, the concordance table provided by the KIPRIS is used to match firm identifiers with patent applicant IDs. The table links patent applicant IDs to corporation registration numbers and business registration numbers. Second, patent applicant IDs are web-scraped from the Korean Patent Office

[24]Throughout the chapter, I use only new patent applications. Other types of applications like extension, modification, or separation of existing patents are dropped to focus on new invention.

[25]Before December 2021, all firms with assets over 7 billion won (6 million USD) were required to be audited.

website using corporation registration numbers. Finally, the final dataset is obtained by merging two datasets and removing duplicate observations. A more detailed matching and data cleaning process can be found in Appendix A.2.

Among these matched firms, the sample is restricted to manufacturing firms with at least one patent application between 2001 and 2007 for the following reasons. First, manufacturing firms are considered as a suitable unit of analysis because manufacturing firms account for 88.0% of the matched patent applications during the sample period, and the China shock affects tradable sectors disproportionately. Second, the sample period begins in 2001 since China joined the WTO in 2001, and the accelerated growth of Chinese exports following the structural changes related to its accession to the WTO is regarded as exogenous shock in the literature (Autor et al., 2013; Pierce and Schott, 2016; Autor et al., 2020a). It is also because South Korea recovered from the Asian Financial Crisis and paid back the bailout package in 2001. The sample period is set to end in 2007 to mitigate possible endogeneity issue arising from the Global Financial Crisis which greatly influenced both trade flows and innovation incentives.

1.3.2 Competition Measures

Competition with China is measured in two dimensions: export competition and import competition. Export competition with China that Korean firm f in industry i experiences at time t is

$$XC_{f,t} = \frac{X_{f,0}}{Y_{f,0}} \sum_{S} \frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}} \frac{X_{i,t}^{CNtoS}}{M_{i,t}^{S}} \times 100 \tag{1.34}$$

where $X_{f,0}$ and $Y_{f,0}$ are firm f's exports and sales at time 0, respectively. Therefore, the first component $\frac{X_{f,0}}{Y_{f,0}}$ shows the firm's reliance on exports. This implies that firms that rely heavily on export markets perceive the rise of Chinese competitors in its export markets more seriously. Turning to the second component, $X_{i,0}^{KRtoS}$ indicates Korean exports to country S in industry i at time 0. Therefore, $\frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}}$ captures the importance of each market S to Korean exports in industry i at time 0. This reflects that competition with Chinese firms in more important export destination country is more influential to exporting firms. Finally, $X_{i,t}^{CNtoS}$ and $M_{i,t}^{S}$ show Chinese exports to country S and the total imports of country S in industry i at time t. Therefore, the last component $\frac{X_{i,t}^{CNtoS}}{M_{i,t}^{S}}$ shows the Chinese share of imports in country S, which is the proxy for competition with China as in the literature (Bloom et al., 2016). In this regard, this measure captures a firm's exposure to export markets and the weighted sum of competition with China in export markets using the importance of each export destination as a weight.

This measure incorporates the firm-level variation with the different initial exposure to export markets and captures industry-level variation with the weighted sum of Chinese share of imports in each export market. Importantly, by keeping firm-level exposure to export markets and the weight of market S fixed at time 0, the time variation of this measure occurs only from the Chinese share of imports in country S, which arises due to the change in China or each importing country S. Similar to Autor et al. (2013) who rely on other countries' imports from China to construct an instrument variable, these changes in third markets are regarded as exogenous to South Korean firms. In other words, the measure of export competition $XC_{f,t}$ is exogenous to Korean firms' innovation decision.

Analogously, import competition that f in industry i faces from the rise of China at time t is

$$IC_{f,t} = \left(1 - \frac{X_{f,0}}{Y_{f,0}}\right) \times \frac{X_{i,t}^{CNtoKR}}{M_{i,t}^{KR}} \times 100 \tag{1.35}$$

Similarly, the reliance on the domestic market is considered to capture the effective level of pressure that a firm faces from the rise of China in its domestic market. Again, this measure includes two sources of variation: the relative initial importance of domestic sales and the time varying industry-level share of imports from China. However, unlike (1.34), this measure may experience endogeneity issue since there could be common factors that affect Korean imports from China and Korean firms' innovation. To mitigate this issue, Japanese imports from China are used to instrument (1.35) following Choi and Xu (2020):

$$ICJP_{f,t} = \left(1 - \frac{X_{f,0}}{Y_{f,0}}\right) \times \frac{X_{i,t}^{CNtoJP}}{M_{i,t}^{JP}} \times 100 \tag{1.36}$$

1.3.3 Data description

Table 1.1 reveals the matching efficiency by showing the number of manufacturing firms, matched manufacturing firms, sample firms, and their share of patents, exports, sales, tangible assets, employment, and profits. It shows that the coverage of matched firms is wide. Among 12,076 manufacturing firms out of 31,178 firms in the KIS-VALUE data, 8,368 firms are matched and 3,960 firms are included in the final dataset. Firms in the sample covers slightly less than two thirds of total corporate innovation and account for at least 74% of exports, sales, tangible assets, employment, and profits of manufacturing firms in the KIS-VALUE dataset.

Table 1.2 reveals that sample firms are heterogeneous in various aspects. First, firms vary in their size. The smallest firm hires only one employee, whereas the largest firm employs 85,813 employees. This heterogeneity is similarly found in terms of age, sales, tangible assets, wages, and profits. Second, firms are different in their reliance on exports. In one extreme, there are firms that only sell in the domestic market, whereas in another extreme, firms make their entire sales from foreign markets. Third, innovation variables show sizable heterogeneity. While firms apply for around 11.7 patents on average each year, the number of application varies between 0 and 16,999. This tendency holds for citation-weighted patent applications,[26] which incorporates the quality of innovation. Finally, the measure of export competition and import competition with China vary significantly across firms.

The heterogeneity becomes more stark when exporting status is considered. Table 1.3 shows the summary statistics of exporting and non-exporting sub-sample firms in columns (1)-(5), and (6)-(10), respectively. Since the measure of export competition and import competition is constructed using the reliance on the export market at the beginning of the sample period, a firm is classified as an exporter when it exports in 2001. Exporting firms tend to be larger in terms of employment, sales, tangible assets, wages, and profits. More importantly, exporting firms apply for about 12 times more patents than non-exporting firms on average. As a result, even though the number of non-exporting firms is almost five times larger than that of exporting firms in the sample, the total number of patent applications by exporting firms is around 2.5 times larger than that of non-exporting firms. Exporters' dominance in innovation is similarly found for citation-weighted patent. This emphasizes one of the reasons why export competition deserves exploration to understand the innovation consequences of the China shock. Since innovation is concentrated on exporters who are disproportionately affected by export competition, export competition is expected to have innovation consequences.

[26]The citation-weighted patent assigns the same value for patents and citations following Trajtenberg (1990). Moreover, since old patents are likely to be cited for a longer time, I only count citations of the first 5 years after the application as in Bloom and Van Reenen (2002).

The importance of exporters in innovation can be also found in Figure 1.2 which shows the evolution of patenting activity in South Korea. The number of patents applied by all applicants, Korea-based corporation, sample firms, and the exporting sub-sample firms have increased over time despite sharp declines in the late 1990s and the late 2000s due to the Asian financial crisis and the global financial crisis. It also reveals that a significant share of patent applications are included in the final dataset through the matching process, and exporting sub-sample covers a considerable share of innovation in the sample.

The heterogeneity in innovation, export competition, and import competition is also found across sectors. Table 1.4 shows how the average number of patent applications changed over the sample period by sectors at the 2-digit industry level. Two things are noticeable. First, the average patent applications vary greatly by industries. For instance, firms in sector 32 (radio, television, and communication equipment and apparatus), 31 (electrical machinery and apparatus), and 34 (motor vehicles, trailers, and semi-trailers) applied for 53.7, 15.7, and 15.7 patents in 2007, whereas firms in sector 19 (leather products and footwear), 18 (apparel), and 20 (wood products, straw, and plaiting materials) applied for 0.6, 0.7, and 0.8 patent in the same year. Second, patenting activity has increased during the sample period in most sectors. Average patent applications in 2007 is larger than in 2001 for all except two sectors.[27] Reflecting this upward trend, the average number of patent applications increases from 7.4 in 2001 to 12.0 in 2007 with 14.6 in 2005 at its peak.

Table 1.5 and Table 1.6 show that export competition and import competition are heterogeneous across sectors.[28] For instance, the average export competition in sector 22 (publication and printing) is zero since there are no exporters in this sector, whereas it is as high as 3.2 in sector 30 (office, accounting and computing machinery) in 2007. In contrast, the average import competition spans from the lowest 6.6 in sector 33 (medical, precision, and optical instruments, watches and clocks) to the highest 73.5 in sector 18 (apparel).[29] In addition, Table 1.5 and Table 1.6 show that both export competition and import competition have intensified during the sample period. On average, export competition and import competition become 1.97 times and 2.53 times larger in

[27] These are 2-digit ISIC sector 19 (leather products and footwear) and 27 (basic metals).

[28] The prevalence of export competition and import competition is shown in Appendix A.3.

[29] The measure of import competition tends to be much larger than that of export competition since there are many non exporters whose measured export competition is zero.

2007 compared to 2001, respectively.

1.4 Empirical Strategies and Estimation Results

1.4.1 Empirical Strategies

The impact of export competition and import competition on innovation is estimated using the measures developed in (1.34) and (1.35). In order to eliminate any unobservable firm-level heterogeneity that affects the innovation outcome, the difference of patent stock between t and $t-1$ or the number of patent applications in year t is used as a dependent variable. Then, the number of average pre-sample period (1995-2000) patent applications is directly controlled in the estimation since firms with larger patent stock tend to apply for more patents. Instead of using the accumulated patent stock, this approach is chosen following Aghion et al. (2022) to avoid putting too much weight on the past invention, which may not be relevant to recent invention. At the same time, since patent applications show a large dispersion across firms and since there are many zeroes, a logarithm is taken after adding one to the number of patent applications.[30]

For competition measures $XC_{f,t}$ and $IC_{f,t}$, Davis-Haltiwanger growth rate $\Delta Y_t = \frac{Y_t - Y_{t-1}}{0.5\times[Y_t + Y_{t-1}]}$ is computed for both shocks for two reasons. First, it eliminates any time-invariant firm-level heterogeneity that affects the level of competition with China. Second, since the measures of export competition and import competition are different in magnitude, they are not directly comparable. By normalizing both measures into the growth rate term, the coefficients in the estimated equations become directly comparable.

In addition, to control for the size of export market,[31] the Davis-Haltiwanger growth rate of the following measure, which is similar to that of Aghion et al. (2018), is included as a control:

$$Xsize_{f,t} = \frac{X_{f,0}}{Y_{f,0}} \sum_{S} \frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}} \ln(M_{i,t}^{S-KR}), \tag{1.37}$$

where $M_{i,t}^{S-KR}$ is the imports of country S from all countries except South Korea. Since (1.37)

[30]Results using alternative methods to deal with the count outcome variable, including Poisson regression and the inverse hyperbolic sine (or arcsinh) transformation, are reported in Section 5.3. Additional results from other specifications can be found in Appendix A.5.

[31]When imports from a country grow in a large magnitude, the effective size of market left for South Korean exporters can be larger even if the Chinese share increases in the country. In this regard, it would be appropriate to control for the market size to examine the competition effect more precisely.

considers the initial importance of each market and the size of each market excluding Korean exports, the growth of this measure captures the exogenous growth of export market size that a firm faces.

The main prediction of the theoretical model is that only high-productivity firms increase innovation in response to stronger competition with China. However, the model leaves the overall impact and the relative importance of export competition and import competition an empirical question. To begin with, the following equation is estimated to examine the overall impact of export competition and import competition with China on innovation:

$$\ln(1+N_{f,t}) = \alpha \Delta XC_{f,t-1} + \beta \Delta IC_{f,t-1} + \gamma \ln(1+N_{f,0}) + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}, \quad (1.38)$$

where $N_{f,t}$ is the new innovation of firm f in year t. In addition to the raw number of patent applications, the number of citation-weighted patents is used to consider the quality of innovation. $\Delta XC_{f,t-1}$, $\Delta IC_{f,t-1}$, and $\Delta Xsize_{f,t-1}$ indicate one-year lagged growth of competition shocks and export market size. A logarithm is taken after adding one to the average pre-sample period (1995-2000) innovation same as the dependent variable. Firm-level time-invariant variables including the average pre-sample period employment, sales, tangible assets (all in logarithms) are added as control variables $X'_{f,0}$. Macroeconomic shocks and sector-specific components are captured by the year fixed effect μ_t and the 2-digit industry fixed effect μ_i. $\varepsilon_{f,t}$ is an error term. Standard errors are clustered at the firm level. The coefficients of interest are α and β, which show the causal impact of competition with China since $\Delta XC_{f,t-1}$ is exogenous by construction, and $\Delta IC_{f,t-1}$ is instrumented with $\Delta ICJP_{f,t-1}$.

Moreover, the following equation is estimated to examine the heterogeneous responses of firms:

$$\begin{aligned}\ln(1+N_{f,t}) = \alpha_1 \Delta XC_{f,t-1} + \alpha_2 \Delta XC_{f,t-1} \times Decile_f + \beta_1 \Delta IC_{f,t-1} + \beta_2 \Delta IC_{f,t-1} \times Decile_f + \\ \zeta Decile_f + \gamma \ln(1+N_{f,0}) + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}, \quad (1.39)\end{aligned}$$

where $Decile_f$ is a 0-9 firm-level labor productivity (sales per employee) decile[32] at the beginning of the sample period within the 2-digit industry.[33] By adding the interaction terms, (1.39) examines

[32] In practice, 0 is assigned to firms whose sales per employee cannot be computed, and 1-9 are assigned to others based on the productivity. Dropping observations without sales per employee information does not change the results.

[33] Sales per employee may not reflect a firm's labor productivity when capital intensity differs significantly by

the heterogeneous impact of competition across firms. More specifically, α_1 captures the innovation response of firms with the lowest productivity to export competition shock, and α_2 captures how firms with higher productivity decile respond. Similarly, β_1 shows the impact of import competition on firms with the lowest productivity, and the heterogeneous responses of firms with higher productivity are captured by β_2. Therefore, α_2 and β_2 are expected to be positive, whereas negative α_1 and β_1 are predicted by the theoretical model.

1.4.2 Main Results

Table 1.7 shows the estimation results of (1.38) including either $\Delta IC_{f,t-1}$, $\Delta XC_{f,t-1}$, or both measures. Columns (2) and (5) show the two-stage least squares (2SLS) results, whereas the rest columns report the ordinary least squares (OLS) results. Two things are noteworthy. First, all coefficients related to import competition are not significant. The overall impact of import competition on innovation, which the theoretical model and the empirical evidence in the literature (Bloom et al., 2016; Autor et al., 2020a) are not clear about, turns out to be indistinguishable from zero in South Korea during the sample period. Second, more interestingly, all coefficients associated with export competition are positive and significant at the 1 percent level. These results imply that the overall innovation response of firms to competition with China is dominated by export competition, and the response is positive, which is new to the literature. These results are striking given the little attention that economists have paid to the role of export competition.

More specifically, in contrast to the insignificant coefficients in columns (1) and (2), column (3) reports that export competition coefficient is 0.514 and significant at the 1 percent level, showing that firms facing more intense export competition with China respond by increasing innovation. The insignificant impact of import competition and the significant impact of export competition is also found in column (4), which includes both import competition and export competition shocks to examine the differential impact of each shock. The coefficient of export competition is precisely estimated and similar to the coefficient in column (3), whereas the import competition coefficient is not distinguishable from zero. The 2SLS results instrumenting $\Delta IC_{f,t-1}$ with $\Delta ICJP_{f,t-1}$ in column (5), which is the most preferred specification, also show that only export competition has

firms. However, this problem is much less severe within the same industry where production technology and therefore capital intensity is similar.

significant and positive impact on innovation at the 1 percent level. Considering the strong first stage F-statistics and the exogeneity of $\Delta XC_{f,t-1}$, this positive and significant relationship can be interpreted as causal.

Quantitatively speaking, the export competition coefficient in column (5) implies that a firm that experiences one standard deviation higher export competition shock (0.074) applies for 0.041 log point more patents. Given that the average patent applications during the sample period is 11.72, this is equivalent to 0.518 more patent.[34] When the average growth rate of export competition between 2001 and 2007 (10.53%) is considered, this implies that tougher export competition explains 18.06% of the innovation increase between 2001 and 2007 compared to the pre-sample period (1995-2000).[35] This evidence shows that the role of export competition is economically meaningful despite it has been rarely discussed.

Table 1.8 shows the heterogeneous impact of competition across firms. Two points are noticeable. First, innovation responses are heterogeneous across firms with different initial productivity, which is consistent with the prediction of the theoretical model. All coefficients of $\Delta IC_{f,t-1}$ and $\Delta XC_{f,t-1}$ except one are negative (though not significant for import competition shocks) and all coefficients related to the interaction of competition shocks and productivity decile are positive. These results indicate that only firms with higher initial productivity increase innovation responding to competition as is predicted by the theoretical model. Second, the innovation responses are dominated by export competition. All coefficients associated with export competition are precisely estimated, whereas import competition coefficients are mostly insignificant. Despite the model's ex-ante ambiguous prediction on the relative importance of import competition and export competition, this empirical evidence highlights the role of export competition again.

More specifically, columns (2) and (3) show that only high-productivity firms increase innovation significantly responding to either import competition or export competition confirming the theoretical prediction. When both shocks are considered at the same time, export competition channel seems to dominate the responses of firms as shown in column (5), the most preferred specification. Quantitatively speaking, column (5) implies that one standard deviation stronger export

[34](1.38) implies that $\frac{\partial \Delta P_{f,t}}{\partial \Delta XC_{f,t-1}} = \beta \times (1 + \Delta P_{f,t})$. Therefore, the effect of ones standard deviation higher export competition shock is computed by $0.550 \times (1 + 11.72) \times 0.074 = 0.518$.

[35]The back of the envelope computation is done as follows. Since the pre-sample period average innovation is 7.64, the contribution of export competition is calculated by $\frac{0.550\times(1+11.72)\times 0.1053}{11.72-7.64} \times 100$.

competition shock leads firms with the lowest initial productivity decile to decrease innovation by 0.047 log point (equivalent to 0.602 patent). Confirming the theoretical prediction, the innovation response to export competition is increasing in initial productivity decile by 0.014 log point (equivalent to 0.182 patent). As a result, the net impact of export competition on innovation becomes positive starting from the fifth decile. When the average annual growth in export competition (10.53%) is considered, these coefficients imply that firms with the lowest productivity decile decrease 0.857 patent application, whereas firms with the highest productivity decile increase 1.469 patent applications facing tougher export competition shocks on average during the sample period.

These results imply that the rise of China increased South Korean firms' innovation, in particular that of high-productivity firms, through the export competition channel during the sample period. The importance of export competition may have arisen due to the absolute size of the export market, the existence of home bias, or different quality preferences in home and foreign markets as mentioned in the theoretical section. In addition, compared to import competition, export competition is expected to capture pure competition effects since increased imports from China at home can have complementary effects to Korean firms using Chinese intermediates, whereas increased imports from China in third markets do not have those effects. Moreover, since both innovation and exports are concentrated on high-productivity firms, export competition may capture the innovation incentives more precisely than import competition when the export competition channel works. One of the concerns is the possible correlation between import competition and export competition. If they are highly correlated, the impact of export competition may partly reflect that of import competition. However, the correlation between $\Delta XC_{f,t-1}$ and $\Delta IC_{f,t-1}$ in the sample is as low as 0.0984, which eases the concern.

1.4.3 Robustness

This section examines possible concerns related to: (i) dependent variable; (ii) existing trend; (iii) sample; and (iv) shocks. The main findings of the previous section, which are the importance of export competition with China, and the concentrated responses on initially more productive firms, are robust to alternative specifications.

(1) Dependent variable

Two concerns may arise from the dependent variable used in the main analysis. First, the number of patent applications may not reflect the quality of innovation. In this regard, the number of citation-weighted patent applications is used as an alternative dependent variable. Second, taking a logarithm after adding one to the number of patent applications could be ad hoc. In order to mitigate this problem, the Poisson regression and the General Method of Moment (GMM) methods are adopted using the number of patent applications as a dependent variable. In addition, the inverse hyperbolic sine transformation is adopted since it is similar to a logarithm retaining zero-valued observations (Burbidge et al., 1988; MacKinnon and Magee, 1990; Pence, 2006).[36]

To begin with the quality of innovation, Table 1.9 shows the results of estimating equation (1.38). Coefficients in column (5), the most preferred specification, show that the response of citation-weighted innovation to export competition is positive and significant, whereas the impact of import competition is estimated as insignificant. Even though the magnitude is slightly different, the results are qualitatively unchanged when the quality of innovation is taken into account. Table 1.10 shows that the citation-weighted innovation based results are qualitatively similar to Table 1.8 when the heterogeneous responses are considered. Again, column (5), the preferred specification, shows that innovation is increasing only for high productivity firms responding only to export competition shocks. The sign of coefficients related to import competition is as expected, though not significant.

Turning to the next concern, the Poisson regression is estimated to deal with the non-negative discrete outcome variable. Using $N_{f,t}$ directly on the left-hand side, the following equation is estimated to examine the overall impact of export competition and import competition on innovation:

$$E[N_{f,t}] = exp\left[\alpha \Delta XC_{f,t-1} + \beta \Delta IC_{f,t-1} + \gamma \ln(1+N_{f,0}) + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i\right], \tag{1.40}$$

where the expected value of patent applications depends on export competition, import competition, pre-sample period innovation, relevant control variables, and fixed effects as in the main analysis. Moreover, since $\Delta IC_{f,t-1}$ may suffer from an endogeneity issue, the two-step General Method of Moment (GMM) method using $\Delta ICJP_{f,t-1}$ as an instrument is also adopted.

[36]The estimation results using research and development (R&D) expenditures are shown in Appendix A.4 focusing on the innovation input.

Table 1.11 shows the results. Columns (1), (3), and (4) show the Poisson regression results, whereas columns (2) and (5) show the GMM estimation results. Similar to the main results, all coefficients associated with export competition are positive and significant at least at the 5 percent level. Column (4) reveals that the impact of import competition is negative and significant. However, this result is sensitive to specification in that import competition coefficient is insignificant when the GMM approach is used in column (5).

In addition, to examine the heterogeneous responses across firms, the following equation is estimated including interaction terms:

$$E[N_{f,t}] = exp[\alpha_1 \Delta XC_{f,t-1} + \alpha_2 \Delta XC_{f,t-1} \times Decile_f + \beta_1 \Delta IC_{f,t-1} + \beta_2 \Delta IC_{f,t-1} \times Decile_f + \zeta Decile_f + \gamma \ln(1 + N_{f,0}) + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i]. \quad (1.41)$$

Table 1.12 shows the results. Consistent with the main findings, innovation responses are governed by export competition, and the heterogeneity is found in that only high-productivity firms increase innovation. All coefficients related to the interaction of export competition shocks and productivity decile are positive and significant, and export competition coefficients without interaction are negative and significant as expected.

Alternatively, the inverse hyperbolic sine transformation is applied to the number of patent applications yielding

$$\widetilde{N}_{f,t} \equiv arcsinh(N_{f,t}) = \ln(N_{f,t} + \sqrt{N_{f,t}^2 + 1}). \quad (1.42)$$

Then, the following equation, which corresponds to the main estimation (1.38), is estimated to investigate the overall impact of competition with China on innovation:

$$\widetilde{N}_{f,t} = \alpha \Delta XC_{f,t-1} + \beta \Delta IC_{f,t-1} + \gamma \widetilde{N}_{f,0} + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}. \quad (1.43)$$

Table 1.13 shows the results that are qualitatively similar to the main results. Overall, export competition increases innovation significantly, whereas the impact of import competition on innovation is not distinguishable from zero. Export competition coefficients are all positive and significant at the one percent level.

Turning to the heterogeneity, to examine the heterogeneous responses between firms with different initial productivity, the following equation is estimated:

$$\widetilde{N}_{f,t} = \alpha_1 \Delta XC_{f,t-1} + \alpha_2 \Delta XC_{f,t-1} \times Decile_f + \beta_1 \Delta IC_{f,t-1} + \beta_2 \Delta IC_{f,t-1} \times Decile_f + \zeta Decile_f + \gamma \widetilde{N}_{f,0} + \delta \Delta Xsize_{f,t-1} + X'_{f,0}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}. \quad (1.44)$$

Table 1.14 shows the results. Consistent with the main findings, innovation is more responsive to export competition than to competition in that most import coefficients are insignificant whereas most export coefficients are significant. In addition, in line with the theoretical prediction, only high-productivity firms increase innovation facing competition with China. All coefficients related to the interaction of export competition shocks and productivity decile are positive and significant, and export competition coefficients without interaction are negative as expected.

(2) Existing trend

As raised by Autor et al. (2020a), the failure in considering existing trend in estimating the impact of the China shock on innovation could be problematic. To mitigate this concern, in addition to controlling the pre-sample period average innovation as in the main analysis, industry-time fixed effects at the 2-digit industry level are included in the estimation to control the sector-specific time trend of innovation within industry, which may drive the main results. Especially because since innovation grows faster in some sectors than others as shown in Table 1.4, incorporating this heterogeneity across sectors could be important. Table 1.15 and Table 1.16 show the results very similar to the main findings. Column (5), the most preferred specification, in both tables show that only export competition related coefficients are significant, and only high-productivity firms increase innovation facing more intense export competition.

(3) Sample

The possibility that the main results are sample-specific is investigated in three ways. First, since the dispersion of innovation between firms is large as shown in Table 1.1, it is possible that few highly innovative firms drive the main findings. To mitigate this concern, firms applied for more than 1000 patents on average during the sample period and firms applied for only one patent during the sample period are dropped from the sample. Table 1.17 and Table 1.18 show that the main conclusion is unaffected by this sub-sample analysis. Only export competition increases innovation, and the responses of firms are heterogeneous in that only high-productivity firms increase innovation facing tougher export competition.

Second, the sample is restricted to manufacturing firms with at least one patent application during the sample period. However, this restriction may lead to the selection of firms that are more likely to engage in innovation actively during the sample period. To examine whether the main results are sensitive to this restriction, all manufacturing firms matched to the patent dataset are used to estimate the impact of competition with China. Table 1.19 and Table 1.20 show qualitatively similar results to the main results. Overall, export competition increases innovation, whereas import competition has null impact on innovation. The heterogeneous responses of firms are found in that only high-productivity firms increase innovation in response to tougher export competition as in the main analysis.

Finally, in the main analysis, the sample begins in 2001 to focus on the exogenous rise of competition with China following the accession of China and ends in 2007 concerning a possible structural break caused by the global financial crisis that might have affected trade flows and innovation behavior of firms. However, the innovation responses found in the main findings could be specific to the sample period. To mitigate this concern, the sample period is extended to 2000-2010. Manufacturing firms with at least one innovation during the new sample period are included in the sample. The results in Table 1.21 and Table 1.22 are not very different from the main results. Export competition continues to dominate the innovation responses, and only high-productivity firms increase innovation. This implies that the stronger role of export competition and the responses concentrated on high-productivity firms are not specific to the sample period between 2001 and 2007.

(4) Shock

To examine whether the results are sensitive to the ways dealing with competition shocks, additional specifications using different lags, an alternative growth rate of competition, and a different method to capture heterogeneity are adopted and estimated.

First, the main analysis assumes that competition with China affects the innovation of firms with one-year lag. However, it is not clear how long it takes to innovate after a negative shock realizes. To examine whether the results are sensitive to the choice of lag, two-year-lagged shocks are used instead of one-year-lagged shocks. Table 1.23 and Table 1.24 show that results are qualitatively similar to the main results. Consistent with the main results, firms increase innovation only responding to export competition shocks, and the response is increasing in initial productivity of firms as is predicted by the model. Firms with the lowest productivity decrease innovation, whereas high-productivity firms increase innovation facing export competition with China.

Second, the main analysis includes the Davis-Haltiwanger growth rate of $XC_{f,t-1}$ and $IC_{f,t-1}$ to measure the change in the intensity of competition with China. Alternatively, the effective change in competition that each firm perceives could be computed with the firm's reliance on domestic/export market and the change in industry-level competition in each market. More specifically, the changes in competition are measured with

$$\frac{X_{f,0}}{Y_{f,0}}\Delta XC_{i,t-1} \quad \text{where} \quad XC_{i,t} = \sum_{S} \frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}} \frac{X_{i,t}^{CNtoS}}{M_{i,t}^{S}} \tag{1.45}$$

$$\left(1 - \frac{X_{f,0}}{Y_{f,0}}\right)\Delta IC_{i,t-1} \quad \text{where} \quad IC_{i,t} = \frac{X_{i,t}^{CNtoKR}}{M_{i,t}^{KR}} \tag{1.46}$$

where Δ indicates the Davis-Haltiwanger growth rate. Similar to the main analysis, the industry-level import competition measure $IC_{i,t}$ is instrumented by the Chinese share of imports in Japan in the same industry:

$$ICJP_{i,t} = \frac{X_{i,t}^{CNtoJP}}{M_{i,t}^{JP}} \tag{1.47}$$

In line with these competition measures, the growth in export market size is measured with

$$\frac{X_{f,0}}{Y_{f,0}}\Delta Xsize_{i,t-1} \quad \text{where} \quad Xsize_{i,t} = \sum_{S} \frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}} \ln(M_{i,t}^{S-KR}) \tag{1.48}$$

Table 1.25 and Table 1.26 report the estimation results using these alternative growth rates. Consistent with the main findings, Table 1.25 shows that export competition significantly increases innovation in all specifications, whereas the impact of import competition is insignificant. Similarly, Table 1.26 shows the results in line with the main findings in that only high productivity firms increase innovation responding to more intense export competition with China. All export competition coefficients related to the interaction terms are positive and precisely estimated, whereas those without interaction terms show negative sign and are significant at the 1 percent level.

Finally, the main results imply that innovation responses are increasing in the productivity decile. To examine whether the results are sensitive to this specification, the impact of competition with China on low-productivity firms and high-productivity firms are directly estimated using the median labor productivity within the 2-digit industry at the beginning of the sample period as a cutoff (represented by dummy variable $high_f$ and low_f). The following equation including interaction terms is estimated:

$$\begin{aligned}\ln(1+N_{f,t}) = \alpha_L\Big(\Delta XC_{f,t-1} \times low_f\Big) + \alpha_H\Big(\Delta XC_{f,t-1} \times high_f\Big) + \beta_L\Big(\Delta IC_{f,t-1} \times low_f\Big) + \\ \beta_H\Big(\Delta IC_{f,t-1} \times high_f\Big) + \zeta high_f + \gamma \Delta X size_{f,t-1} + \delta \ln(1+N_{f,0}) + X'_{f,0}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}.\end{aligned} \tag{1.49}$$

α_L captures the innovation response of relatively low-productivity firms to export competition shock, and α_H shows how high-productivity firms respond to export competition shock. Similarly, β_L and β_H reveal the impact of import competition on firms with low-productivity and high productivity firms, respectively. Table 1.27 shows that only high-productivity firms increase innovation responding to export competition. The decrease in innovation by low-productivity firms becomes not clear. However, the strong and positive impact of export competition on high productivity firms remains the same for all specifications, which is consistent with the main results.

1.4.4 Extension

(1) Enlargement of the European Union

The theoretical model predicts that only high-productivity firms increase innovation to escape from competition. However, the overall impact of competition and the relative importance of import competition and export competition are ex-ante ambiguous. Therefore, the positive impact export competition on innovation, and the stronger response to export competition could be specific to competition with China. In this regard, I explore the enlargement of the European Union (EU) in 2004 and 2007 to check the external validity of the main findings.

In 2004 and 2007, the EU experienced the largest enlargement in terms of territory, number of states, and population after its establishment in 1993. Ten Eastern European countries including Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia acceded to the EU in 2004, while Bulgaria and Romania, who did not meet the requirements in 2004 joined the EU in 2007 (European Commission, 2009). As a result of the enlargement, trade integration within new member states themselves and with old member states deepened rapidly. The share of imports from new member states among the total imports of the EU[37] increased from 6.6% to 10.5% between 2004 and 2015. At the same time, the exports of new member states to non-EU countries increased as well due to the common trade policy applied to EU member states and the productivity growth followed by the integration. Between 2004 and 2015, the share of Korean imports from new EU member states increased from 0.3% to 0.7%. In order to examine the impact of stronger competition with these new EU member states in the European markets and the domestic market on South Korean firms, the following measures of import competition and export competition with new EU member states are constructed:

$$XC^{eu}_{f,t} = \frac{X_{f,0}}{Y_{f,0}} \sum_{S \in EU} \frac{X^{KRtoS}_{i,0}}{\sum_{S' \in EU} X^{KRtoS'}_{i,0}} \frac{X^{NEWtoS}_{i,t}}{M^{S}_{i,t}} \times 100 \tag{1.50}$$

$$IC^{eu}_{f,t} = \left(1 - \frac{X_{f,0}}{Y_{f,0}}\right) \frac{X^{NEWtoKR}_{i,t}}{M^{KR}_{i,t}} \times 100. \tag{1.51}$$

$X^{NEWtoS}_{i,t}$ indicates the exports of new EU member states to country S. Note that only EU markets are considered in computing $XC^{eu}_{f,t}$ to focus on markets where competition intensified the most.

In estimating equation (1.38) and (1.39), sample is restricted to manufacturing firms with at least one innovation between 2004 and 2015. $\Delta IC^{eu}_{f,t}$ is instrumented by $\Delta ICJP^{eu}_{f,t}$ as in the main estimation, and pre-sample period (1998-2003) average patent applications along with relevant control variables are included. The growth of market size $\Delta Xsize_{f,t-1}$, year fixed effects, and 2-digit industry time effects are also controlled. In addition, 0-9 productivity decile is defined at the beginning of the sample period (2004) within the 2-digit ISIC level.

Table 1.28 shows that all coefficients related to export competition with new EU member states in European markets are positive and significant at the 1 percent level, whereas import competition coefficients are not significant. These results reveal that South Korean manufacturing firms increase innovation responding to export competition with new EU member states. In contrast,

[37] 27 EU member states at the end of 2007 are included. The accession of Croatia in 2013 and the exit of the United Kingdom in 2015 are not considered.

the overall impact of import competition with new EU member states on the innovation of Korean manufacturing firms is indistinguishable from zero during the sample period.

Table 1.29 shows the heterogeneous innovation responses of firms to competition with new EU member states. These results confirm the external validity of the main findings and the theoretical model. The heterogeneous responses to competition shocks are found in line with the China shock analysis and the theoretical prediction. The sign of coefficients imply that low-productivity firms decrease innovation and high-productivity firms increase innovation facing stronger competition with new EU member states. As in the main analysis, this responses are stronger and more consistent facing export competition. The coefficients of interaction between export competition and the productivity decile are all positive and significant at the 5 percent level, whereas those of import competition are not significant.

(2) Quality Implications of Competition

The theoretical model suggests that firms innovate to produce higher quality product facing tougher competition with China. Therefore, to complete the discussion, it is ideal to show that the competition-induced innovation leads to the increase in product quality at the firm-level. However, to infer the quality of product that each firm produces, firm-level pricing information is necessary, which the current chapter is lack of. As a second best approach, I explore the industry-level quality implications of innovation induced by competition with China.

To begin with, the industry-level product quality is proxied by the inflation adjusted unit value of industry-level exports considering multiple export markets and the importance of each market. More specifically, since there are many export destination countries, the reliance of Korean exports on each market and the unit value of products exported to those markets are explicitly considered as follows. First, the unit values of exports are computed for each market at the 4-digit ISIC level. Second, using the reliance of Korean exports to each market as a weight, the weighted sum of these market-specific unit values of exports is computed at the industry-level. Finally, by deflating this industry-level weighted unit value with the producer price index (PPI),[38] the industry-level product

[38]Since the PPI relies on a different classification system, which is not tightly matched to 4-digit ISIC system, the PPI at the 2-digit industry level is used to deflate the unit value of exports.

quality measure is finalized. More formally, the industry-level quality of product is defined as

$$Quality_{i,t} = \sum_{S} \frac{X_{i,0}^{KRtoS}}{\sum_{S'} X_{i,0}^{KRtoS'}} \times \frac{X_{i,t}^{KRtoS}}{Q_{i,t}^{KRtoS}} \times \frac{PPI_{i,0}}{PPI_{i,t}}, \tag{1.52}$$

where the first component is the time-invariant weight of each country S, which is the same weight used to construct the export competition measure. The second component indicates the unit value of Korean exports to country S in industry i since $Q_{i,t}^{KRtoS}$ denotes the volume of Korean exports to country S at time t. The third component deflates the unit value of exports using the PPI.[39]

Equipped with this industry-level product quality measure, the impact of competition with China on product quality through innovation is examined in two steps. First, after aggregating up firm-level data at the industry-level, the predicted value of industry-level innovation $\widehat{\ln(1+N_{i,t})}$ is computed by running the first regression:

$$\ln(1+N_{i,t}) = \alpha\Delta IC_{i,t-1} + \beta\Delta XC_{i,t-1} + \gamma\Delta Xsize_{i,t-1} + \delta\ln(1+N_{i,0}) + X'_{i,0}\Lambda + \mu_t + \mu_i + \varepsilon_{i,t}, \tag{1.53}$$

where $\Delta IC_{i,t-1}$, $\Delta XC_{i,t-1}$, $\Delta Xsize_{i,t-1}$ are the Davis-Haltiwanger growth rate of the industry-level $IC_{i,t-1}$, $XC_{i,t-1}$, $Xsize_{i,t-1}$ which are defined in (1.46), (1.45), and (1.48), respectively. Similar to the main analysis, $\Delta IC_{i,t-1}$ is instrumented by $\Delta ICJP_{i,t-1}$, and the industry-level pre-sample period average number of patent applications, employment, sales, and tangible assets are controlled. Time fixed effects and the 2-digit industry fixed effects are also included in the estimation.

Second, using the predicted number of patent applications from the first regression, the second regression estimates the following equation:

$$\Delta Quality_{i,t} = \beta_I \widehat{\ln(1+N_{i,t})} + \varepsilon_{i,t}. \tag{1.54}$$

where $\Delta Quality_{i,t}$ is the Davis-Haltiwanger growth rate of product quality. Standard errors are clustered at the 4-digit industry-level. Since $\widehat{\ln(1+N_{i,t})}$ captures the industry-level innovation induced by competition with China, which is predicted to increase product quality, β_I is expected to be positive.

[39] The weighted unit value of exports may not reflect the quality of product sold in the domestic market. However, since innovation benefits all products regardless of destination, the change in product quality induced by innovation is assumed to be similar for products sold in the domestic market and the export markets.

Table 1.30 shows the result of this estimation. As is expected, the coefficient of interest is positive and significant at the 1 percent level. This evidence suggests that innovation induced by competition with China increase the quality of product consistent with the prediction of the theoretical model.

1.5 Conclusion

How does the rise of China affect innovation in other countries? In answering this question, I emphasize the importance of *export competition*, which means competition in third countries. Since export competition with China has intensified significantly due to the worldwide rise of Chinese exports, abstracting away from this channel could be misleading in understanding the effects of the China syndrome. However, surprisingly, this channel has been rarely explored in the literature.

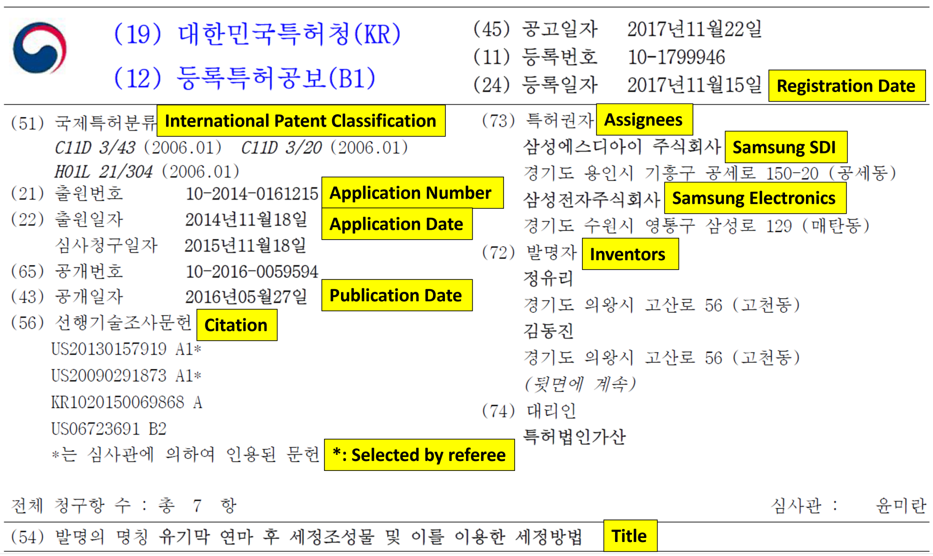
To understand the export competition channel, I develop a multi-country model with innovation incorporating quality preferences of consumers and heterogeneous productivity of firms. The model predicts that more intense competition increases innovation of high-productivity firms, whereas it decreases innovation of low-productivity firms. This is because the downward pressure on profits prevents low-productivity firms from innovating even though quality preferences of consumers encourage firms to innovate.

Empirical evidence from South Korean patent data using a novel firm-level measure of export competition developed in this chapter confirms the model's predictions by showing that only high-productivity firms increase innovation in response to more intense competition with Chinese firms. While this tendency is found for both export competition and import competition, the results are more consistent for export competition. In addition, the empirical evidence answers to the model's ambiguous prediction on the overall impact and the relative importance of export competition and import competition. Only export competition increase innovation during the sample period, and innovation is more responsive to export competition than to import competition.

This study can be extended to several interesting directions. First, the readily applicable measure of export competition developed in this chapter can be used to explore other outcomes and/or other countries with better data. Considering the worldwide growth of Chinese exports over the past decades, there is no reason to limit the scope of research to innovation consequences of competition with Chinese firms that South Korean firms face. For instance, the labor market consequences of export competition including, but not limited to, the skill composition of workforce worth investigating since the change in innovation is likely to affect the labor demand of firms. Second, other competitive shocks can be explored to expand our understandings of export competition. Considering numerous historical episodes including trade liberalization, free trade agreements, industrial policies, and commodity discoveries, the rise of competition in third markets should not be rare. Third, the factors that make firms respond more strongly to export competition than to import competition requires further investigation both theoretically and empirically. The relative importance of candidates including the market size, home bias, and different quality preferences across countries suggested in this study could be analyzed with a better data source that covers firm-level pricing information and export destination information.

1.A Figures

Figure 1.1: Patent information example



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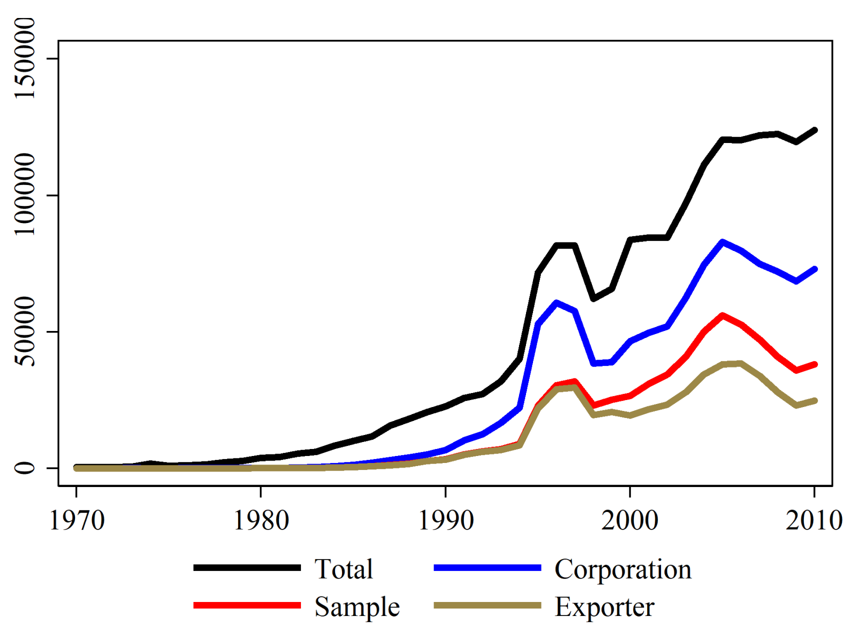
(54) 발명의 명칭 유기막 연마 후 세정조성물 및 이를 이용한 세정방법 Title

Notes: Translation is added by the author in yellow boxes.

Figure 1.2: The number of patent applications



1.B Tables

Table 1.1: Matching results

	Firms (count) (1)	Patents (%) (2)	Exports (%) (3)	Sales (%) (4)	Tangible assets (%) (5)	Employment (%) (6)	Profits (%) (7)
KIS-VALUE	31,178	76.2	-	-	-	-	-
Manufacturing	12,076	67.0	100	100	100	100	100
Matched mfg	8,368	67.0	99.3	92.6	94.0	91.1	92.6
Sample	3,960	64.8	86.8	78.0	80.1	74.0	81.5

Notes: Firms in row 2 are manufacturing firms in the KIS-VALUE dataset. They are the sub-sample of firms in row 1. Firms in row 3 are manufacturing firms with patent IDs, and row 4 includes manufacturing firms in the sample. Column (2) shows the contributions to the total Korea based corporate patent applications (in %) over the sample period. Columns (3)-(7) indicate the share of matched manufacturing firms and sample firms to the full manufacturing firms in the KIS-VALUE dataset (in %) over the sample period. Firms are designated to sectors based on the time-invariant KSIC9 industry classification.

Table 1.2: Sample summary statistics

Variable	Obs.	Mean	SD	Min	Max
Year	25,875	2004.12	1.98	2001	2007
Age	25,875	12.53	11.32	0	110
Employment	21,794	268.72	1,835.14	1	85,813
Sales (millions USD)	24,510	109.33	1,152.94	0.00007	67,992.6
Tangible assets (millions USD)	24,643	42.42	481.56	0.00015	32,047.4
Wages (millions USD)	24,570	3.13	25.28	0.00002	1,229.0
Profits (millions USD)	24,683	8.26	143.56	-1000.88	10,506.7
Exports/sales (%)	25,875	0.06	0.18	0	1.00
Patent applications	25,875	11.72	265.72	0	16,999
Citation-weighted patent	25,875	20.58	468.73	0	28,886
XC	25,875	0.49	2.20	0	39.14
IC	25,875	13.40	14.85	0	87.44

Notes: Sample includes manufacturing firms with at least one patent applications between 2001 and 2007. The year of application is used as the year of patenting for patent applications and citation-weighted patents.

Table 1.3: Sample summary statistics by exporting status in 2001

	Exporting firms in 2001					Non-exporting firms in 2001				
Variable	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max
Year	4,284	2004	2.00	2001	2007	21,591	2004.15	1.98	2001	2007
Age	4,284	23.23	14.50	0	110	21,591	10.41	9.20	0	78
Employment	4,259	834.65	3,892.62	3	85,813	17,535	131.27	639.84	1	31,633
Sales (millions USD)	4,277	439.63	2,579.34	0.12	67,992.56	20,233	39.51	419.79	0.00007	25,293.74
Tangible assets (millions USD)	4,277	187.13	1,124.19	0.01	32,047.64	20,366	12.03	99.59	0.00015	5,192.77
Wages (millions USD)	4,253	10.76	52.57	0.07	1,229.04	20,317	1.53	13.41	0.00002	949.07
Profits (millions USD)	4,284	37.41	340.66	-1,000.88	10,506.65	20,399	2.14	18.82	-346.38	1,092.67
Exports/sales (%)	4,284	0.28	0.30	0	1.00	21,591	0.01	0.09	0	1.00
Patent applications	4,284	50.47	558.01	0	16,999	21,591	4.03	149.97	0	12,248
Citation-weighted patent	4,284	87.14	979.73	0	28,886	21,591	7.37	268.01	0	20,317
XC	4,284	2.98	4.67	0	39.14	21,591	0	0	0	0
IC	4,284	9.72	11.81	0	76.79	21,591	14.14	15.27	0	87.44

Notes: Sample includes manufacturing firms with at least one patent applications between 2001 and 2007. The year of application is used as the year of patenting for patent applications and citation-weighted patents.

Table 1.4: Average patent applications in each industry

ISIC	Description	2001	2002	2003	2004	2005	2006	2007	Δ(01-07)
15	Food products and beverages	0.951	0.769	0.89	0.787	0.848	0.901	1.608	0.657
17	Textiles	0.633	0.843	0.808	0.774	0.593	0.727	1.732	1.099
18	Apparel	0.231	0.357	0.429	0.2	0.267	0.867	0.667	0.436
19	Leather products and footwear	0.875	0	0	0.6	0	1	0.6	-0.275
20	Wood products, straw, and plaiting materials	0.375	0.375	0.211	0.474	1.053	1	0.842	0.467
21	Paper and paper products	0.282	0.381	0.442	0.372	0.455	0.659	0.977	0.695
22	Publishing, printing and reproduction of recorded media	0.353	0.176	0.294	0.5	0.333	0.278	0.889	0.536
23	Coke and refined petroleum products	1	1.538	1	0.462	0.462	1.846	9.286	8.286
24	Chemicals and chemical products	2.256	2.041	2.584	2.802	3.44	4.398	4.441	2.186
25	Rubber and plastics products	0.662	0.698	1.664	1.946	2.02	2.17	2.715	2.053
26	Other non-metallic mineral products	0.804	0.621	1.102	1.28	1.294	1.627	1.806	1.001
27	Basic metals	21.893	16.837	9.69	5.634	6.289	8.437	8.882	-13.012
28	Fabricated metal product	0.724	0.636	0.803	0.812	1.05	1.272	1.341	0.617
29	Machinery and equipment	2.274	2.203	3.068	2.837	3.624	4.476	5.265	2.991
30	Office, accounting and computing machinery	0.565	1.519	1.179	1.172	1.667	1.7	1.733	1.168
31	Electrical machinery and apparatus	9.443	13.013	18.058	26.225	26.937	25.015	15.656	6.212
32	Radio, television and communication equipment and apparatus	28.417	45.712	54.491	68.645	78.152	63.701	53.701	25.284
33	Medical, precision and optical instruments, watches and clocks	1.841	1.326	1.255	1.575	2.038	2.876	3.425	1.583
34	Motor vehicles, trailers and semi-trailers	12.268	13.088	13.84	14.249	11.89	13.481	14.082	1.814
35	Other transport equipment	8.184	9.412	8.304	10.544	10.93	12.702	15.655	7.471
36	Furniture	0.877	1.228	1.863	2.952	4.209	4.506	3.341	2.464
Total		7.354	9.447	10.975	13.356	14.572	13.448	12.004	4.650

Note: This table shows the average number of patent applications by firms in each 2-digit ISIC industry. Manufacturing firms with at least one patent application between 2001 and 2007 are included.

Table 1.5: Average export competition in each industry

ISIC	Description	2001	2002	2003	2004	2005	2006	2007	Δ(01-07)
15	Food products and beverages	0.276	0.266	0.268	0.277	0.289	0.308	0.3	0.023
17	Textiles	0.702	0.796	0.904	1.023	1.122	1.205	1.227	0.525
18	Apparel	0.007	0.007	0.008	0.007	0.009	0.009	0.01	0.003
19	Leather products and footwear	0.948	0.85	0.961	1.048	1.073	1.142	0.789	-0.160
20	Wood products, straw, and plaiting materials	0.063	0.086	0.077	0.09	0.108	0.146	0.149	0.086
21	Paper and paper products	0.266	0.289	0.347	0.369	0.429	0.491	0.55	0.285
22	Publishing, printing and reproduction of recorded media	0	0	0	0	0	0	0	0.000
23	Coke and refined petroleum products	0.215	0.235	0.288	0.245	0.278	0.271	0.273	0.058
24	Chemicals and chemical products	0.218	0.232	0.256	0.283	0.326	0.347	0.415	0.197
25	Rubber and plastics products	0.437	0.457	0.469	0.497	0.539	0.577	0.606	0.169
26	Other non-metallic mineral products	0.064	0.084	0.093	0.096	0.13	0.162	0.148	0.084
27	Basic metals	0.394	0.423	0.451	0.61	0.66	0.825	0.846	0.451
28	Fabricated metal product	0.382	0.404	0.423	0.462	0.51	0.551	0.592	0.210
29	Machinery and equipment	0.111	0.122	0.136	0.151	0.17	0.187	0.259	0.148
30	Office, accounting and computing machinery	1.009	1.3	1.847	2.238	2.538	2.757	3.159	2.150
31	Electrical machinery and apparatus	0.7	0.773	0.847	0.899	0.945	1.02	1.111	0.411
32	Radio, television and communication equipment and apparatus	0.789	0.931	1.065	1.27	1.507	1.709	1.833	1.045
33	Medical, precision and optical instruments, watches and clocks	0.159	0.17	0.187	0.206	0.226	0.231	0.272	0.112
34	Motor vehicles, trailers and semi-trailers	0.075	0.088	0.093	0.136	0.176	0.217	0.249	0.173
35	Other transport equipment	0.302	0.384	0.345	0.368	0.48	0.622	0.717	0.415
36	Furniture	0.84	0.921	1.006	1.088	1.168	1.241	1.333	0.492
Total		0.335	0.375	0.415	0.476	0.540	0.601	0.662	0.327

Note: This table shows the average export competition that firms experience in each 2-digit ISIC industry. Manufacturing firms with at least one patent application between 2001 and 2007 are included.

Table 1.6: Average import competition in each industry

ISIC	Description	2001	2002	2003	2004	2005	2006	2007	Δ(01-07)
15	Food products and beverages	15.306	15.204	16.213	15.472	17.251	18.529	19.08	3.774
17	Textiles	28.752	31.609	32.758	34.69	37.823	41.112	42.732	13.980
18	Apparel	67.115	72.792	73.645	75.712	73.139	74.726	73.531	6.417
19	Leather products and footwear	33.292	39.641	41.611	44.541	45.242	45.579	44.008	10.716
20	Wood products, straw, and plaiting materials	27.974	29.934	31.316	37.077	34.998	35.547	34.838	6.863
21	Paper and paper products	8.41	10.527	9.118	10.49	19.505	26.814	31.951	23.540
22	Publishing, printing and reproduction of recorded media	6.632	7.866	10.619	13.489	15.743	22.564	27.469	20.837
23	Coke and refined petroleum products	11.222	11.161	10.015	8.83	9.868	9.281	9.93	-1.293
24	Chemicals and chemical products	4.864	5.289	5.725	5.994	6.615	7.369	8.733	3.869
25	Rubber and plastics products	6.165	9.111	8.481	9.943	11.385	13.65	14.166	8.001
26	Other non-metallic mineral products	18.151	22.61	25.843	31.909	28.484	33.211	40.487	22.336
27	Basic metals	7.405	7.771	9.487	15.207	18.973	22.551	23.924	16.519
28	Fabricated metal product	12.69	16.176	18.074	21.048	29.211	33.083	36.238	23.548
29	Machinery and equipment	3.254	4.197	4.725	5.751	7.75	9.088	11.99	8.736
30	Office, accounting and computing machinery	12.063	13.775	23.626	35.468	41.274	42.102	46.862	34.798
31	Electrical machinery and apparatus	16.548	19.838	20.985	22.811	25.257	28.231	32.682	16.134
32	Radio, television and communication equipment and apparatus	8.921	11.034	10.188	11.691	13.804	20.721	27.723	18.803
33	Medical, precision and optical instruments, watches and clocks	1.479	2.075	2.776	2.842	3.912	4.052	6.604	5.125
34	Motor vehicles, trailers and semi-trailers	2.109	2.491	3.031	4.095	6.686	11.241	16.073	13.963
35	Other transport equipment	6.248	10.442	5.739	9.725	15.069	17.158	19.574	13.326
36	Furniture	19.057	22.8	30.681	37.77	44.789	50.125	52.464	33.408
Total		8.076	9.666	10.357	12.056	14.382	17.216	20.452	12.376

Note: This table shows the average import competition that firms experience in each 2-digit ISIC industry. Manufacturing firms with at least one patent application between 2001 and 2007 are included.

Table 1.7: Overall impact of competition with China on innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.028	0.070		0.013	-0.089
	(0.017)	(0.136)		(0.018)	(0.152)
$\Delta XC_{f,t-1}$			0.514***	0.509***	0.550***
			(0.131)	(0.132)	(0.149)
1st stage F-statistics		72.098			62.217
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.8: Heterogeneous impact of competition with China on innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.015	-0.346		0.006	-0.231
	(0.035)	(0.219)		(0.035)	(0.227)
$\Delta IC_{f,t-1} \times Decile_f$	0.008	0.080*		0.002	0.027
	(0.007)	(0.041)		(0.007)	(0.044)
$\Delta XC_{f,t-1}$			-0.730**	-0.734**	-0.640*
			(0.357)	(0.358)	(0.376)
$\Delta XC_{f,t-1} \times Decile_f$			0.203***	0.203***	0.193***
			(0.059)	(0.060)	(0.062)
Cutoff decile for IC	3	6	-	6	10
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		36.795			30.993
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.9: Overall impact of competition with China on citation-weighted innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.027	0.149		0.007	-0.055
	(0.023)	(0.175)		(0.023)	(0.196)
$\Delta XC_{f,t-1}$			0.687***	0.684***	0.710***
			(0.159)	(0.161)	(0.181)
1st stage F-statistics		72.101			62.226
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of citation-weighted patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.10: Heterogeneous impact of competition with China on citation-weighted innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.007	-0.468		0.021	-0.313
	(0.047)	(0.293)		(0.047)	(0.301)
$\Delta IC_{f,t-1} \times Decile_f$	0.007	0.119**		-0.003	0.049
	(0.009)	(0.052)		(0.009)	(0.054)
$\Delta XC_{f,t-1}$			-0.975**	-0.983**	-0.862*
			(0.449)	(0.451)	(0.470)
$\Delta XC_{f,t-1} \times Decile_f$			0.272***	0.273***	0.254***
			(0.073)	(0.073)	(0.075)
Cutoff decile for IC	3	6	-	9	8
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		36.782			30.994
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of citation-weighted patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.11: Count outcome: Overall impact of competition with China on innovation

	Poisson (1)	GMM (2)	Poisson (3)	Poisson (4)	GMM (5)
$\Delta IC_{f,t-1}$	-0.050	-0.149		-0.126**	-0.272
	(0.069)	(0.252)		(0.056)	(0.202)
$\Delta XC_{f,t-1}$			0.790**	0.949***	1.135**
			(0.365)	(0.361)	(0.493)
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the (pseudo) Poisson maximum likelihood estimation results, whereas columns (2) and (5) report the GMM estimation results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.12: Count outcome: Heterogeneous impact of competition with China on innovation

	Poisson (1)	GMM (2)	Poisson (3)	Poisson (4)	GMM (5)
$\Delta IC_{f,t-1}$	0.191	-0.384		0.324	0.833
	(0.320)	(1.753)		(0.307)	(1.082)
$\Delta IC_{f,t-1} \times Decile_f$	-0.028	0.026		-0.053	-0.128
	(0.035)	(0.208)		(0.033)	(0.125)
$\Delta XC_{f,t-1}$			-4.258*	-4.522**	-4.833**
			(2.229)	(2.246)	(2.310)
$\Delta XC_{f,t-1} \times Decile_f$			0.587**	0.640**	0.699***
			(0.254)	(0.254)	(0.258)
Cutoff decile for IC	8	-	-	8	8
Cutoff decile for XC	-	-	9	9	8
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the (pseudo) Poisson maximum likelihood estimation results, whereas columns (2) and (5) report the GMM estimation results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.13: Overall impact of competition with China on innovation (arcsinh)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.032	0.082		0.014	-0.114
	(0.021)	(0.166)		(0.022)	(0.186)
$\Delta XC_{f,t-1}$			0.636***	0.630***	0.681***
			(0.156)	(0.158)	(0.178)
1st stage F-statistics		72.130			62.240
N	17,721	17,721	17,721	17,721	17,721

Notes: The inverse hyperbolic sine transformed number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.14: Heterogeneous impact of competition with China on innovation (arcsinh)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.017	-0.416		0.007	-0.286
	(0.044)	(0.272)		(0.044)	(0.282)
$\Delta IC_{f,t-1} \times Decile_f$	0.010	0.096*		0.002	0.032
	(0.008)	(0.050)		(0.009)	(0.052)
$\Delta XC_{f,t-1}$			-0.814*	-0.818*	-0.702
			(0.432)	(0.434)	(0.456)
$\Delta XC_{f,t-1} \times Decile_f$			0.237***	0.236***	0.224***
			(0.071)	(0.071)	(0.074)
Cutoff decile for IC	3	6	-	6	10
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		36.805			31.000
N	17,721	17,721	17,721	17,721	17,721

Notes: The inverse hyperbolic sine transformed number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.15: Overall impact of competition with China on innovation (sector-year FE)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.039	0.223*		0.022	0.125
	(0.026)	(0.131)		(0.026)	(0.134)
$\Delta XC_{f,t-1}$			0.546***	0.540***	0.512***
			(0.136)	(0.137)	(0.140)
1st stage F-statistics		115.644			112.771
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, sector-year fixed effects, where sector is classified as 2-digit ISIC industry. The pre-sample period (1995-2000) average of innovation, sales, employment, tangible assets (all in logarithms) are also included. Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.16: Heterogeneous impact of competition with China on innovation (sector-year FE)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.007	-0.214		0.013	-0.058
	(0.039)	(0.211)		(0.039)	(0.216)
$\Delta IC_{f,t-1} \times Decile_f$	0.009	0.085**		0.002	0.034
	(0.007)	(0.041)		(0.007)	(0.043)
$\Delta XC_{f,t-1}$			-0.698*	-0.702*	-0.678*
			(0.360)	(0.362)	(0.372)
$\Delta XC_{f,t-1} \times Decile_f$			0.203***	0.202***	0.192***
			(0.060)	(0.060)	(0.062)
Cutoff decile for IC	2	4	-	1	3
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		49.011			47.598
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, sector-year fixed effects, where sector is classified as 2-digit ISIC industry. The pre-sample period (1995-2000) average of innovation, sales, employment, tangible assets (all in logarithms) are also included. Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.17: Overall impact of competition with China on innovation (winsorized)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.026	0.028		0.012	-0.151
	(0.020)	(0.163)		(0.021)	(0.187)
$\Delta XC_{f,t-1}$			0.479***	0.475***	0.535***
			(0.138)	(0.140)	(0.163)
1st stage F-statistics		53.324			44.583
N	13,894	13,894	13,894	13,894	13,894

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least two patent applications between 2001 and 2007. Firms applied for more than 1000 patents on average are dropped. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.18: Heterogeneous impact of competition with China on innovation (winsorized)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.027	-0.480		-0.006	-0.341
	(0.044)	(0.293)		(0.044)	(0.306)
$\Delta IC_{f,t-1} \times Decile_f$	0.010	0.096*		0.004	0.035
	(0.008)	(0.054)		(0.008)	(0.059)
$\Delta XC_{f,t-1}$			-0.576	-0.575	-0.446
			(0.385)	(0.387)	(0.412)
$\Delta XC_{f,t-1} \times Decile_f$			0.170***	0.169***	0.156**
			(0.062)	(0.063)	(0.068)
Cutoff decile for IC	4	6	-	3	-
Cutoff decile for XC	-	-	5	5	4
1st stage F-statistics		27.068			20.371
N	13,894	13,894	13,894	13,894	13,894

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least two patent application between 2001 and 2007. Firms applied for more than 1000 patents on average are dropped. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.19: Overall impact of competition with China on innovation (no sample restriction)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.021	0.047		0.007	-0.104
	(0.013)	(0.113)		(0.014)	(0.125)
$\Delta XC_{f,t-1}$			0.547***	0.544***	0.590***
			(0.117)	(0.118)	(0.132)
1st stage F-statistics		81.299			70.105
N	25,151	25,151	25,151	25,151	25,151

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.20: Heterogeneous impact of competition with China on innovation (no sample restriction)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.011	-0.213		0.004	-0.149
	(0.025)	(0.167)		(0.025)	(0.171)
$\Delta IC_{f,t-1} \times Decile_f$	0.006	0.050		0.001	0.006
	(0.005)	(0.031)		(0.005)	(0.032)
$\Delta XC_{f,t-1}$			-0.582*	-0.584*	-0.522
			(0.316)	(0.317)	(0.328)
$\Delta XC_{f,t-1} \times Decile_f$			0.185***	0.184***	0.182***
			(0.053)	(0.053)	(0.055)
Cutoff decile for IC	3	6	-	7	-
Cutoff decile for XC	-	-	5	5	4
1st stage F-statistics		39.644			35.629
N	25,151	25,151	25,151	25,151	25,151

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.21: Overall impact of competition with China on innovation (longer sample period)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.040***	0.113		0.018	-0.074
	(0.014)	(0.095)		(0.015)	(0.110)
$\Delta XC_{f,t-1}$			0.676***	0.667***	0.710***
			(0.132)	(0.134)	(0.150)
1st stage F-statistics		208.609			186.298
N	29,544	29,544	29,544	29,544	29,544

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1994-1999) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2000 and 2010. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.22: Heterogeneous impact of competition with China on innovation (longer sample period)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.013	-0.072		0.015	-0.034
	(0.029)	(0.134)		(0.030)	(0.143)
$\Delta IC_{f,t-1} \times Decile_f$	0.011*	0.035		0.001	-0.011
	(0.006)	(0.023)		(0.006)	(0.025)
$\Delta XC_{f,t-1}$			-0.585	-0.591	-0.573
			(0.415)	(0.418)	(0.436)
$\Delta XC_{f,t-1} \times Decile_f$			0.198***	0.198***	0.205***
			(0.065)	(0.065)	(0.069)
Cutoff decile for IC	3	4	-	1	-
Cutoff decile for XC	-	-	4	4	4
1st stage F-statistics		103.857			93.267
N	29,544	29,544	29,544	29,544	29,544

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1994-1999) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2000 and 2010. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.23: Overall impact of competition with China on innovation (2-year lagged shocks)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-2}$	0.025	0.292*		0.011	0.136
	(0.017)	(0.153)		(0.017)	(0.171)
$\Delta XC_{f,t-2}$			0.575***	0.570***	0.521***
			(0.132)	(0.133)	(0.155)
1st stage F-statistics		78.017			68.616
N	17,550	17,550	17,550	17,550	17,550

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the 2-year lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.24: Heterogeneous impact of competition with China on innovation (2-year lagged shocks)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-2}$	-0.031	-0.016		-0.006	0.085
	(0.032)	(0.224)		(0.032)	(0.235)
$\Delta IC_{f,t-2} \times Decile_f$	0.011*	0.058*		0.004	0.010
	(0.006)	(0.035)		(0.007)	(0.037)
$\Delta XC_{f,t-2}$			-0.652*	-0.651*	-0.693*
			(0.361)	(0.364)	(0.384)
$\Delta XC_{f,t-2} \times Decile_f$			0.199***	0.197***	0.195***
			(0.061)	(0.061)	(0.065)
Cutoff decile for IC	4	2	-	3	1
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		40.043			35.266
N	17,550	17,550	17,550	17,550	17,550

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the 2-year lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.25: Overall impact of competition with China on innovation (alternative growth)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\left(1-\frac{X_{f,0}}{Y_{f,0}}\right)\Delta IC_{i,t-1}$	0.004	-0.167		0.011	-0.113
	(0.018)	(0.139)		(0.018)	(0.137)
$\frac{X_{f,0}}{Y_{f,0}}\Delta XC_{i,t-1}$			1.342***	1.346***	1.303***
			(0.392)	(0.391)	(0.389)
1st stage F-statistics		75.420			73.309
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.26: Heterogeneous impact of competition with China on innovation (alternative growth)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\left(1-\frac{X_{f,0}}{Y_{f,0}}\right)\Delta IC_{i,t-1}$	0.020	-0.099		-0.001	-0.184
	(0.037)	(0.220)		(0.036)	(0.216)
$\left(1-\frac{X_{f,0}}{Y_{f,0}}\right)\Delta IC_{i,t-1}\times Decile_f$	-0.003	-0.012		0.003	0.013
	(0.007)	(0.041)		(0.007)	(0.040)
$\frac{X_{f,0}}{Y_{f,0}}\Delta XC_{i,t-1}$			-3.731***	-3.738***	-3.810***
			(1.261)	(1.258)	(1.254)
$\frac{X_{f,0}}{Y_{f,0}}\Delta XC_{i,t-1}\times Decile_f$			0.757***	0.759***	0.764***
			(0.197)	(0.196)	(0.195)
Cutoff decile for IC	8	-	-	2	-
Cutoff decile for XC	-	-	6	6	6
1st stage F-statistics		36.399			35.492
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.27: Heterogeneous impact of competition with China on innovation (above/below median)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1} \times low_f$	0.021	-0.155		0.020	-0.207
	(0.023)	(0.152)		(0.023)	(0.163)
$\Delta IC_{f,t-1} \times high_f$	0.032	0.263		0.007	0.021
	(0.026)	(0.189)		(0.027)	(0.214)
$\Delta XC_{f,t-1} \times low_f$			0.138	0.131	0.209
			(0.227)	(0.228)	(0.245)
$\Delta XC_{f,t-1} \times high_f$			0.673***	0.671***	0.663***
			(0.162)	(0.164)	(0.186)
1st stage F-statistics		35.848			27.251
N	17,721	17,721	17,721	17,721	17,721

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. $high_f$ (low_f) is an indicator for firms above (below) the median productivity within 2-digit industry at the beginning of the sample period. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.28: Overall impact of competition with East European countries on innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC^{eu}_{f,t-1}$	-0.005	-0.072		-0.006	-0.078
	(0.005)	(0.050)		(0.005)	(0.050)
$\Delta XC^{eu}_{f,t-1}$			0.434***	0.435***	0.444***
			(0.106)	(0.107)	(0.109)
1st stage F-statistics		90.225			89.754
N	52,532	52,532	52,532	52,532	52,532

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1998-2003) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2004 and 2015. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.29: Heterogeneous impact of competition with East European countries on innovation

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC^{eu}_{f,t-1}$	-0.009	-0.178*		-0.009	-0.180*
	(0.009)	(0.104)		(0.009)	(0.103)
$\Delta IC^{eu}_{f,t-1} \times Decile_f$	0.001	0.023		0.001	0.023
	(0.002)	(0.020)		(0.002)	(0.019)
$\Delta XC^{eu}_{f,t-1}$			-0.346	-0.344	-0.324
			(0.293)	(0.293)	(0.291)
$\Delta XC^{eu}_{f,t-1} \times Decile_f$			0.120**	0.120**	0.118**
			(0.048)	(0.048)	(0.047)
Cutoff decile for IC^{eu}	-	-	-	-	-
Cutoff decile for XC^{eu}	-	-	4	4	4
1st stage F-statistics		18.083			17.928
N	52,532	52,532	52,532	52,532	52,532

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1998-2003) average of innovation, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2004 and 2015. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 1.30: Quality implications of competition with China

β_I	0.0150***
	(0.0041)
N	770

Notes: This table shows the estimation result of (1.54). ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Chapter 2

Knowledge Spillovers: Evidence from Innovation Cities in South Korea

2.1 Introduction

Economic activity is spatially concentrated. It is widely accepted that the positive externality of agglomeration plays an important role in concentration, though the specific mechanisms are still in question. One of the candidates is knowledge spillovers, which yield positive intellectual externalities both through formal and informal interaction within locality, and therefore improve productivity. Empirical evidence suggests that an increased interaction through new infrastructure, including the improvement of roads (Agrawal et al., 2017), airline proximity (Giroud, 2013), and high-speed railway (Wang and Cai, 2020), which decreases the effective distance between places, improves productivity or increases innovation, which indirectly implies the existence of knowledge spillover effects. However, more direct evidence on local knowledge spillovers is less abundant for two reasons. First, people, firms, and other entities choose the best location endogenously. This makes it difficult to evaluate the causal effect of agglomeration on knowledge spillovers because finding appropriate counterfactual is not straightforward due to the endogeneity. Second, it is not clear how to measure knowledge production and its spillovers. This chapter tackles these difficulties in four directions.

First, a quasi-experimental increase in local agglomeration, the relocation of public agencies to Innovation Cities in South Korea is investigated and a winner-loser comparison is conducted. In 2003, South Korean government announced plans to relocate public agencies including state-owned enterprises, government-funded research institutes, and government affiliated organizations (henceforth, relocated agencies) from Seoul metropolitan area to provincial areas to promote balanced regional growth. The agencies to relocate were determined in 2005, and the location of 10 Innovation Cities[1] to relocate the agencies were announced in the same year. The construction of infrastructure began in 2007, and the relocation of 112 public agencies and 41,364 jobs started in 2012 and completed in 2019. Since the decision of relocation was not made by relocated agencies, but by central and local governments to promote balanced growth, this Innovation City Project provides a distinct opportunity to study the the spillover effects of regional development policies suffering less from selection and endogeneity issue. Moreover, the information about other candidate municipalities that were not selected as Innovation Cities is used to conduct a winner-loser comparison of innovation outcomes. This strengthens a causal inference by setting a more appropriate control group.

Second, the universe of South Korean patent data is used to construct municipality-level knowledge production. Since patenting in Innovation Cities increases automatically when public agencies move in, patent applications are classified by the relevance with the relocated agencies to distinguish the direct impact of relocation of public agencies and its spillover effects on the change in regional innovation. The direct and mechanical impact of relocation is measured with solo work by relocated agencies, whereas its spillovers are measured by patenting of local agencies. Local agencies' patenting is decomposed further by their co-work with relocated agencies, which reveals more direct spillover effects, and their work irrelevant with relocated agencies. Equipped with this observable information, whether the relocation of public agencies has local knowledge spillovers or not is directly examined.

Third, to capture the heterogeneity between Innovation Cities more precisely, a continuous treatment intensity variable is developed considering when each relocated agency moved and how many patents they applied for prior to the relocation. Regressions using this treatment intensity variable is expected to capture the impact of relocation of public agencies more precisely than the difference-in-differences (DiD) method for at least two reasons. First, each relocated agencies has different innovation capacity and therefore different potential for knowledge spillovers. This heterogeneity in the magnitude of shock is appropriately captured by the continuous treatment intensity variable. Second, the relocation of public agencies did not happen at once. This staggered and

[1] Since one Innovation City may span multiple municipalities, relocated agencies moved to 14 municipalities.

gradual relocation is explicitly taken into account by the treatment intensity variable. This is an important benefit of using the relocation of public agencies compared to other regional development policies examined in the literature[2] since the physical relocation of public agencies allows to take advantage of the pre-relocation information of those relocated agencies to incorporate the heterogeneous magnitude and the timing of shock on each Innovation City precisely.

Finally, to examine the spatial scope of spillover effects beyond Innovation Cities, the magnitude of innovation capacity relocated to each municipality's neighborhood is measured using the distance between each municipality and Innovation Cities. More specifically, using the treatment intensity variable, the innovation capacity relocated within certain distance is computed for different levels of distance. Then, whether these innovation capacity relocated to each municipality's neighborhood affects its innovation is examined to see whether knowledge spillover effects beyond Innovation Cities exists. Since interactions between municipalities are expected to be decreasing in distance due to the traveling cost, the spillover effects beyond Innovation Cities are likely to be diminishing in distance if they exist.

The empirical evidence can be summarized as follows. First, the relocation of public agencies increases the total number of patent applications in Innovation Cities. This increase includes an increase in innovation by relocated agencies themselves, and the co-work of local agencies with the relocated agencies, which reveals increased interactions and spillovers. However, local innovation irrelevant with relocated agencies does not increase as a result of relocation, which implies that spillovers in Innovation Cities happen mostly through the co-work between relocated agencies and local agencies not by improving innovation environments. Interestingly, even though the solo-work of relocated agencies decreases after relocation, the increase in co-work between local agencies and relocated agencies offsets the loss of solo-work so that relocating one potential innovation to Innovation Cities generates more than one innovation in Innovation Cities. Second, the positive knowledge spillover effects beyond Innovation Cities are found but relatively sensitive to specifications. In addition, whenever they exist, they are limited to very close regions indicating that knowledge spillover effects are locally concentrated.

The remaining part of this chapter proceeds as follows. Section 2.2 reviews related literature.

[2] For instance, the construction of new universities Andrews (Forthcoming) and new factories Greenstone et al. (2010) have been examined.

Section 2.3 introduces the historical background and the progress of the Innovation City project. Section 2.4 describes the data. Section 2.5 introduces the empirical strategies, and Section 2.6 reports the results. Section 2.7 concludes.

2.2 Related Literature

It is useful to distinguish the agglomeration effect from the spillover effect. The agglomeration effect means that the economic activity of interest becomes more active when more economic agents are concentrated in a place since concentration generates positive externalities. In contrast, spillover effect means the externality itself that an economic agent or an economic activity generates and influences other agents by the economic activity of interest. Therefore, the first order and efficient goal of a place-based development policy is to generate large positive spillovers in a target region to attract other agents that enjoy the spillover effects so that the agglomeration economy grows in a virtuous cycle. In this regard, what drives a large positive spillover effect under what condition is a very import question for policy makers.

Greenstone et al. (2010) show that the opening of a large manufacturing plant generates positive productivity spillover effect on local incumbent firms, especially whose economic distance represented by the labor pool and the technological linkage is closer to the new plant. Kline and Moretti (2014a) examines the long-run impact of a large scale infrastructure development policies in Tennessee Valley region, finding that gains in manufacturing employment persist, but national agglomeration gains are limited since the gains in the region are offset by the losses in the rest of the country. Researchers also have examined place-based policies providing tax incentives or subsidies to attract investments to designated districts including industrial zones, free trade zones, empowerment zones, and more under different names globally. Many of them focus mostly on labor market outcome and productivity (see Kline and Moretti (2014b) for a survey).

The existence of knowledge spillover effect and its geographical localization has been well recognized (Jaffe, 1986, 1989; Jaffe et al., 1993a). However, many of early works rely on the equilibrium variation and are not free from the endogeneity issue. To resolve the endogeneity issue, more recent work take advantage of the quasi-experimental variation to examine the regional spillover effect. One of the common examples of the quasi-experiment adopted in the literature is the opening of universities. In addition to the exogeneity of shocks, it has advantages in exploring the knowledge spillover effects since universities generate new knowledge. For instance, Andersson et al. (2009) examine the Swedish university decentralization policy and the establishment of new universities in regions without universities to mitigate the endogeneity problem. They also use instrument variables to strengthen the causal inference. Using patent data to estimate the impact of universities on local innovation, they find positive impact, which sharply attenuates with distance. However, they cannot distinguish the direct activities of a university from the spillover effect on nearby research-intensive industry including the effect through producing higher productivity graduates. Similarly, Cowan and Zinovyeva (2013) find positive impact of universities on regional innovation relying on the creation of new universities in Italy using patent data. More recently, Andrews (Forthcoming) analyzes the impact of opening new universities on local innovation using U.S. data. A winner-loser comparison similar to Greenstone et al. (2010) suggests that local invention increases mostly due to the population increase.

However, universities are not the only entity that create new knowledge. In this regard, I focus on the government-led relocation of public sector relying on its quasi-experimental setting in exploring the knowledge spillover effect. I am not the first in studying the impact of public sector relocation. However, to my knowledge, this is the first study that examines the innovation consequences of the relocation of public sector focusing on knowledge spillover effect. In contrast, this strand of literature focuses on the local labor market impact. For instance, Faggio and Overman (2014) focus on the relocation of 25,000 civil service jobs out of London and Southern East toward other regions. They find that the increase in public sector employment in the relocated region leads to a small insignificant increase in total private employment since an increase in non-tradable employment in the region is offset by a decrease in tradable employment. Examining these results further, Faggio (2019) show that only private service job that supports relocated people increases near the relocated public service office, and the impact decreases in distance. More recently, Becker et al. (2021) show that the relocation of German federal government from Berlin to Bonn increases public employment in Bonn significantly, relative to control group of cities, whereas private employment increases only modestly. In summary, this strand of literature find that the labor market impact is weak, limited to jobs supporting the relocated sectors, and diminishing in distance.

The contributions of the current chapter to the literature are threefold. First, this chapter complements the knowledge spillover literature with the causal evidence, which is still insufficient. Second, it adds the under-studied innovation consequences to the relocation of public institutes literature. Finally, the empirical evidence expands our understandings on the impact of Innovation City project in South Korea by shedding lights on the innovation. Even though the impact on employment (Jeon and Lee, 2021) and on Gross Regional Domestic Product (GRDP) and population (Kim, 2017) has been studied, the innovation consequences have not been explored yet.

2.3 Background

The rapid growth and industrialization of South Korea after the 1960s was supported by the industrial policies represented by the 'selection and concentration' strategy to maximize the efficiency to use scarce resources. It allowed the country to grow out of poverty in an unprecedented pace but accelerated the regional concentration to Seoul metropolitan area, the capital region at the same time. As of 2000, 46.3% of the population[3], 47.2% of GRDP[4], 74% of patent applications[5], and 91% of top 100 firms[6] were concentrated in Seoul metropolitan area, which accounts for only 12.6% of South Korean area.

Concerning this imbalance, the 16th South Korean president Roh Moo Hyun promised to promote the balanced regional growth during the election campaign. Winning the election in 2003, Roh administration announced guidelines for the relocation of public agencies including state-owned enterprises, government-funded research institutes, and government affiliated organizations outside the capital region. In 2004, the basic principles and implementation direction of relocation were publicized, which conceptualizes the Innovation City as a city that facilitates collaboration and networking between relocated agencies, enterprises, universities, and research institutes supported by the innovation-friendly environment and city infrastructure. The size of cities was planned to house 20,000-50,000 residents gradually including 2,500-4,000 employees of relocated agencies and the relocation of relevant industries.

Since the Innovation City project was a part of the balanced national development strategy, it was planned to develop one Innovation City per one province except Seoul metropolitan area

[3]Source: Statistics Korea.
[4]Source: Statistics Korea.
[5]Source: Korean Intellectual Property Organization.
[6]Source: Ministry of Land, Infrastructure, and Transportation.

(Seoul, Incheon, and Kyeonggi-do), Daejeon, and Chungcheongnam-do. Seoul metropolitan area was automatically excluded since public agencies were moving out of the region, whereas Daejeon and Chungcheongnam-do were excluded since Daejeon had the second government complex, and Roh administration were planning to construct a new administrative capital in Chungcheongnam-do. In addition to the 'one Innovation City one province' rule, the balance in the size and the number of public agencies allocated to each province was also emphasized since balance and equality were important determinants, which sometimes incurred political conflicts and the change in original plans. For instance, Chungcheongbuk-do was not considered as a province to relocate public agencies in the original project since it is close to a planned new administrative capital. However, since Korean Constitutional Court ruled that the Special Act for the Construction of New Administrative Capital was against the constitution in 2004, 12 public agencies were assigned to relocate to Chungcheongbuk-do to complement its loss.

In 2005, the central government finalized and shared the guidelines on the site selection with local governments. Each local government constituted the site selection committee to determine the location of Innovation City within the region based on the guidelines shown in Table 2.1. Since Gwang-ju and Jeollanam-do agreed to develop one Innovation City together, 10 Innovation Cities were selected among 86 candidates, which span 14 municipalities. However, even after the site selection was complete, the Innovation City project kept changing. For instance, Korea Land Corporation (KLC) and Korea National Housing Corporation (KNHC) were planned to relocate to Kyeongsangnam-do and Jeollabuk-do, respectively. However, as a part of the government-led state-owned enterprise advancement plan, KLC and KNHC were merged to be Korea Land and Housing Corporation (LH) in 2009. After two years of conflict between two provinces to attract LH, one of the largest relocating agencies, it was determined to relocate LH to Kyeongsangnam-do. To compensate the loss of Jeollabuk-do, the government decided to relocate National Pension Fund, which was initially assigned to Kyeongsangnam-do, to Jeollabuk-do in 2011.

Moreover, the Innovation City project itself was reconsidered by Lee Myung-bak administration, which inherited Rho administration, since Lee administration focused more on the deregulation of Seoul metropolitan area and the privatization of state owned enterprises. On April 16th, 2008, the Ministry of Land, Transport and Maritime Affairs mentioned the difficulties to continue the Innovation City project, which was followed by the cease of residential land supply for Innovation

Cities. On May 3rd, 2008, the president Lee said that "the centralized construction of Innovation City seems not proper since each province has different environments" and asked each province to propose in which direction the Innovation City project should be modified. It was widely considered as requesting a reexamination of the project. However, the overall reexamination of the project was not followed since local governments and politicians protested strongly against this action. In the end, the relocation of public agencies started in 2012 and completed in 2019, 7 years delayed than the original plan. In total, 112 public agencies with 41,364 employees relocated to 10 innovation cities.[7]

Considering the relatively weak emphasis on the economic rationale of the Innovation City project, frequent modification of the original plans, the delayed timing of relocation, and the mandated physical relocation, the Innovation City project in this chapter is regarded as quasi-experimental, and the relocation of agencies to Innovation Cities are considered as exogenous shock to municipalities throughout the chapter. Nevertheless, possible endogeneity will be thoroughly considered in the analysis.

2.4 Data

2.4.1 Data Sources

South Korean municipality-level innovation data spanning 17 years (2003-2019) are constructed in this paper. The period of interest is set between 2003 and 2019 since the Innovation City project was initiated when president Roh Moo Hyun was elected in 2003, and the relocation of public agencies was complete in 2019.[8] The universe of Korean patent data, which is the measure of innovation in this paper, is sourced from Korea Intellectual Property Rights Information Service (KIPRIS). Each patent has unique application number, the name and the address of applicants with IDs, and citation information among others. I use the reported address of each applicant for each patent to assign patents to municipalities. Since multiple applicants from different municipalities may co-apply for the same patent, I allow double counting of patents treating all applicants independently. For instance, when a patent has two applicants from region A and one applicant from region B, the

[7] The number of firms relocated to each province/metro city is: Busan (13), Daegu (10), Gwangju-Jeollanam-do (16), Ulsan (9), Gangwon-do (12), Chungcheongbuk-do (11), Jeollabuk-do (12), Kyeongsangbuk-do (12), Kyeongsangnam-do (11), Jeju (6).

[8] Moreover, since it takes time for patent applications to be public, more recent data may miss patent applications.

number of innovation in region A and region B are counted as two and one, respectively. Correcting errors, typos, and misreporting, the municipality-level location of 2,283,085 out of 2,283,268 patents filed by domestic applicants are identified allowing double counting between 2003 and 2019.

Information on the list of Innovation Cities, relocated agencies, and the year of their relocation is sourced from the official website of innovation city managed by the Ministry of Land, Infrastructure, and Transportation.[9] Patent information of these relocated agencies is identified using the corporation registration number and business registration number of relocated agencies matched to the patent applicant IDs. Furthermore, I requested and obtained the information about the number of relocated employee upon relocation to the Ministry of Land, Infrastructure, and Transportation per Official Information Disclosure Act. Similarly, the information about other candidates of Innovation Cities is provided by local governments per my request. Since Busan constructed Innovation Cities by redeveloping old central districts, there are no other candidates in Busan. All other local governments provided information about other candidate municipalities, and four of them clarified runner-up candidates.

Municipality-level variables including population, the number of four-years universities, and the number of four-years university instructors are sourced from Statistics Korea. In addition, municipality-level employment information is constructed using South Korean Census on Establishments. This administrative dataset contains the establishment-level employment by industry and municipality. Since the industry classification has been revised over the sample period, from the 8th revision of Korean Standard Industry Classification (KSIC) to 10th revision, I link the 8th revision and 10th revision of KSIC to the 9th revision of KSIC following the concordance table provided by Statistics Korea. Since firms in different industries may have different innovation opportunities and incentives, industries are categorized by six large sectors: agriculture, fishery, and mining; manufacturing; construction; personal services; business services; other. Table 2.2 shows specific industries categorized to each sector.

The distance between municipalities and Innovation Cities is measured as the linear distance between the centroid of municipalities and Innovation Cities. In doing so, the location of an Innovation City is defined as the centroid of relocated agencies in the Innovation City. To reflect the change in administrative division, all municipality-level data are aggregated to a larger region

[9] https://innocity.molit.go.kr

when merge or split happened during the sample period. For instance, since Changwon, Masan, and Jinhae merged to be one city in 2010, the number of patent applications of three cities are aggregated and considered as that of one municipality even before 2010. Similarly, Cheongwon and Cheongju, Namjeju and Seogwipo, Bukjeju and Jeju, Nonsan and Gyeryong, Goesan and Jeungpyeong are aggregated respectively. Yeongi is regarded as Sejong even before the establishment of Sejong city.

2.4.2 Data Description

Figure 2.1 shows the location of Innovation Cities and other candidates. Reflecting the 'one Innovation City in one province' rule, Innovation Cities represented by red diamonds are evenly distributed across 10 provinces and metropolitan cities outside the Northwest region in black color. Blue dots show the location of runner-up candidates, and green triangles represent other candidates.

Figure 2.2 shows how the number of patent applications and its regional distribution evolve from 2003 to 2019. The left map shows that patent applications in 2003 are geographically concentrated in the Northwest region including Seoul metropolitan area. Southeast coast is another region active in innovation, though it is not comparable to Seoul metropolitan area. The right map shows the number of patent applications in 2019. Compared to the left map, two things are noteworthy. First, patent applications increase in many regions. Second, while the dominance of northwest region continues, several new innovation centers emerge. Reflecting this dispersion, the share of patent applications of Seoul metropolitan area decreased from 72.9% to 62.5% between 2003 and 2019.[10] To explore the emergence of new clusters further, the change in the number of patent applications between 2003 and 2011, and 2011 and 2019 are shown in Figure 2.3 together with the location of Innovation Cities since the first relocation to Innovation Cities happened in 2012. The right map reveals that Innovation Cities and their close neighborhood experienced faster increase in innovation between 2011 and 2019 compared to other regions. However, this tendency is not clearly found in the left map. Indeed, the increase in patent applications between 2011 and 2019 in Innovation Cities account for 50.5% of the increase outside the Northwest region, whereas Innovation Cities account for 13.4% of the increase between 2003 and 2011 in the same region. This suggests that the relocation of agencies may have contributed to the increase in Innovation Cities.

[10] The share of the Northwest region (Seoul metropolitan area, Chungcheongnam-do, and Daejeon) decreased from 79.7% to 72.9% between 2003 and 2019.

Though this evidence shows that the relocation of public agencies to Innovation Cities could have positive association with innovation in Innovation Cities, more careful investigation is needed for two reasons. First, the relocation of agencies automatically increase the number of patent applications in Innovation Cities simply by changing their address from Seoul metropolitan area to Innovation Cities. Therefore, it is necessary to dissect this increase in innovation into the mechanical increase of relocation and the spillover effect to understand this phenomenon more clearly. More specifically, regional innovation could increase as a result of the spillover when local agencies collaborate more with relocated agencies, which is more direct, or as innovation environments improve, which is more indirect. In this regard, I classify patent applications into solo applications by relocated agencies, joint applications by relocated agencies and local agencies, and other applications by local agencies unrelated to relocated agencies. Second, since endogenous selection of Innovation Cities is possible, an appropriate comparison group should be chosen for a causal inference on the innovation impact of relocation. Following Greenstone et al. (2010) and Andrews (Forthcoming), this chapter adopts a winner-loser comparison method, where losing municipalities are either runner-up candidates or all other candidates.

Considering these two issues, Table 2.3 shows the changes in the number of patent applications by type of patent applications and region for two sub-sample periods. Columns (1)-(4) show the changes between 2003 and 2011, whereas columns (5)-(8) show the changes between 2011 and 2019. First, as is clear from columns (1) and (5), the overall innovation in Innovation Cities is increasing faster between 2011 and 2019 than between 2003 and 2011. Given the slow-down of innovation in other regions, this acceleration is remarkable. Second, columns (2) and (6) reveal this acceleration of innovation in Innovation Cities is importantly driven by the solo-works of relocated agencies moved from the Northwest region. Between 2011 and 2019, solo-works decrease in the Northwest region and increase in Innovation Cities. This relocation of solo-works accounts for 85.2% of the acceleration of innovation in Innovation Cities between two sub-periods. Third, columns (3) and (7) show that co-work with relocated agencies increased in Innovation Cities, which shows a direct spillover effect of relocation. The increase in co-works in Innovation Cities between 2011 and 2019 is significantly larger compared to the first sub-period and accounts for 25.4% of the accelerated innovation in Innovation Cities. Therefore, the solo-works of relocated agencies and their co-works with local agencies explain more than 100% of the acceleration of innovation in Innovation

Cities.[11] Importantly, the increase in solo-works is not observed for runner-up municipalities and other candidate municipalities, and the increase in co-works is much weaker or not observed for comparison groups. Finally, it is not clear whether there exists the indirect spillover effect beyond co-work since columns (4) and (8) show that the change in innovation irrelevant with relocated agencies is smaller in the second sub-period than the first sub-period. However, since this requires a further investigation since this deceleration is much stronger in runner-up municipalities and other candidate municipalities. In other words, it is possible that this type of innovation decreases less in Innovation Cities compared to comparison groups due to the indirect spillover effects from the relocation.

Table 2.4 shows how different Innovation Cities are from other candidate municipalities and the rest municipalities between 2003 and 2011 before the relocation started. For the number of university and university instructors, the average between 2006 and 2011, and 2007 and 2011 are used due to the data coverage. Columns (1)-(4) show the mean of municipality characteristics for Innovation Cities, runner-up municipalities (Runner-up), all non-winner candidate municipalities including runner-up municipalities (Candidate), and all non-Northwest municipalities (Full). Columns (5)-(7) show the t statistics for the difference in means. The runner-up municipalities seem to be the closest comparison group of Innovation Cities even though they are statistically different from Innovation Cities for several variables including the employment share of manufacturing and the number of universities. Importantly, the number of patent applications in runner-up municipalities is not statistically different from Innovation Cities. Therefore, if innovation increases in Innovation Cities after the relocation of public agencies compared to runner-up municipalities, this may not be due to the advantages that Innovation Cities already have. In terms of innovation, the candidate municipalities are also comparable to Innovation Cities, whereas non-Northwest municipalities are statistically different from Innovation Cities. In this regard, though not as close as the runner-up municipalities, the candidate municipalities are also used to check robustness of the estimation to add more observations in the empirical analysis.

[11] The contribution of solo-work is computed by $\frac{(4330-2248)}{1773} \times 100$, whereas that of co-work is computed by $\frac{(4330-2248)}{(535-7)} \times 100$

2.5 Empirical strategies

2.5.1 Within Innovation Cities

The impact of relocating public agencies to Innovation Cities on municipality-level innovation is estimated using two approaches: difference-in-difference (DiD) method and regressions using a continuous treatment variable. To examine the importance of setting appropriate control groups, the impact is explored for different set of comparison groups. More specifically, municipalities compared to Innovation Cities are either all other non-Northwest municipalities, other candidate municipalities, or runner-up municipalities.

First, a difference-in-difference (DiD) method is used to estimate whether the relocation of public agencies affects innovation and whether it has knowledge spillover effects in Innovation Cities. More formally, the following equation is estimated:

$$y_{mt} = \beta InnCity_m \times Treat_{mt} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{2.1}$$

where the municipality-level y_{mt} includes the total number of patent applications, solo patent applications by relocated agencies, joint applications by relocated agencies and local agencies, and other applications by local agencies classifying the type of innovation by its relevance with relocated agencies. $InnCity_m$ is an indicator of municipalities that public agencies relocate to, and $Treat_{mt}$ is one from the year when the first relocation happens for each municipality. Municipality fixed effects δ_m, year fixed effects μ_t, and municipality-level controls X_{mt} including population, employment (in logarithms), the employment share of manufacturing, the employment share of business service, and the number universities are included in the regression. Standard errors ε_{mt} are clustered at the province level. The coefficient of interest is β.

However, this standard DiD may not perfectly capture the impact of relocation for two reasons. First, since each public agency relocated to Innovation Cities at different time, the intensity of treatment is heterogeneous both within and across Innovation Cities. Figure 2.4 shows the number of agencies relocated to each Innovation City by year. Since relocation proceeded gradually, it took seven years to complete, and the speed of relocation was different for each Innovation City. Second, each relocated agency has different innovation potential and therefore heterogeneous innovation impact on Innovation Cities. To mitigate these concerns and to capture the intensity of relocation more precisely, a continuous treatment variable is developed using how many patents each relocated agency applied for prior to the relocation. More specifically, the innovation potential of each relocated agency is proxied by the three-year average number of patent applications before the relocation.[12] Then, this innovation potential of each relocated agency is accumulated at the municipality level as agencies relocate to Innovation Cities. Formally, for municipality m, the relocated innovation potential at time t is

$$IP_{mt} = \mathbf{1}(\, m \in Innovaion\ City\,) \sum_{j} (avgInn_j \times relocation_{mjt}) \tag{2.2}$$

where $\mathbf{1}()$ is an indicator function that is one only if m is one of the Innovation Cities. $avgInn_j$ is relocated agency j's average number of patent applications within three years before the relocation. This time-invariant variable measures the pre-relocation innovation capacity of each relocated agency. A dummy variable $relocation_{mjt}$ is one when j is in municipality m at time t. For instance, suppose agency A with 100 average patent applications and agency B with 50 average patent applications moved to Innovation City m in 2013 and 2014, respectively. Then, $IP_{mt}=0$ for $t<2013$ since relocation does not happen yet. Then, as agency A relocated in 2013, innovation potential changes to $IP_{m,2013} = 100$, and it increases to $IP_{m,2014} = 150$ as agency B moves in 2014. Since there is no further relocation after 2014, $IP_{mt}=150$ for $t>2014$. Figure **??** shows the accumulated innovation potential relocated to each Innovation City by year. By combining both heterogeneous innovation potential of relocated agencies and the timing of relocation, this measure shows that the intensity of shock (relocated innovation potential) varies between Innovation Cities, within Innovation Cities, and across time. Equipped with this continuous treatment intensity variable, the following regression is estimated to examine the impact of relocation:

$$y_{mt} = \beta IP_{mt} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{2.3}$$

where the coefficient of interest if β. Similar to the DiD regression, municipality fixed effects δ_m, year fixed effects μ_t, and municipality-level control variables are included in the regression.

[12] If an agency relocates at time t, then the innovation potential of the agency is proxied by the average number of patent applications in $t-1$, $t-2$, and $t-3$.

Standard errors ε_{mt} are clustered at the province level.

2.5.2 Beyond Innovation Cities

Not only agencies in the Innovation Cities bu also local agencies in municipalities close to Innovation Cities can also enjoy increased interactions with relocated agencies, which implies the possibility of spillovers beyond Innovation Cities. However, since spillovers are more likely to happen when there exist frequent interactions, the spillover effects are expected to be decreasing in distance, if they exist. Therefore, to explore the spatial scope of spillover effects beyond the Innovation Cities, the physical distance and the innovation potential relocated to Innovation Cities are used. More specifically, the magnitude of innovation potential relocated to each municipality's neighborhood is measured using the distance to Innovation Cities as follows:

$$IPdistance_{mt}^{d} = \sum_{i} IP_{it} \times \mathbf{1}(\,distance_{im} < d\,), \tag{2.4}$$

where $\mathbf{1}(\,distance_{im} < d\,)$ is one when the centroid of a municipality m is less than $d\,km$ away from Innovation City i.[13] The distance between municipality m and Innovation City i is set to be zero when $m = i$. Figure 2.6 show the distance from each municipality to the nearest Innovation City. For a given distance d and time t, this measure tends to be larger when a municipality is closer to Innovation Cities and when relocated innovation potential to those Innovation Cities is larger. To be realistic, this measure allows knowledge spillovers from multiple Innovation Cities.

Equipped with these measures, the following equation is estimated similar to Faggio (2019):

$$y_{mt} = \beta_0 IP_{mt} + \sum_{d} \beta_d IPdistance_{mt}^{d} + \delta_m + \mu_t + X'_{mt}\Lambda + \varepsilon_{mt}, \tag{2.5}$$

where y_{mt} is the measure of knowledge spillovers. In this estimation, all non-Northwest municipalities including Innovation Cities are included in the estimation since spillover effects are not limited to candidate municipalities or runner-up municipalities and can happen between Innovation Cities. To control the direct effect of relocation on Innovation City itself, IP_{mt} is added as a control variable. The spillover effects are captured by β_d. To examine the scope of the spillover effects,

[13] The location of Innovation City is defined as the centroid of relocated agencies instead of the centroid of municipality.

$IPdistance^{d}_{mt}$ with $d = 5, 15, 30, 50$ are used.[14] Municipality fixed effects δ_m, year fixed effects μ_t, municipality-level control variables are also included. Standard errors are clustered at the province level.

2.6 Results

2.6.1 Within Innovation Cities

Table 2.5 shows the estimation results of (2.1) using different types of innovation and different control groups. Classifying patents with the relevance with relocated agencies, each row reports the estimated β using the total number of patent applications, solo work by relocated agencies, co-work with relocated agencies, and other patents irrelevant with relocated agencies as dependent variables. Control groups used in columns (1)-(2) are all other municipalities in the non-Northwest region, whereas they are restricted to candidate municipalities in columns (3)-(4) and to runner-up municipalities in columns (5)-(6), respectively. Columns (2), (4), and (6) include the number of universities in each municipality as a control variable, which shortens the sample period from 2003-2019 to 2006-2019.

The results are sensitive to the control group emphasizing the importance of choosing an appropriate comparison group. Columns (1) and (2) show that the relocation of public agencies increases total innovation, solo innovation by relocated agencies, and the co-work of relocated agencies and local agencies in Innovation Cities significantly, whereas the impact of relocation on innovation unrelated to relocated agencies is statistically not distinguishable from zero. Coefficients in column (1) shows that as a result of the relocation of public agencies, the total number of patent applications in Innovation Cities increases by 140.2 compared to other municipalities on average, and this increase is decomposed into an increase of solo-work by 74.8, an increase of co-work by 19.3, and an insignificant increase in other work by 46.1. However, when a comparison group is restricted to other candidate municipalities in columns (3) and (4), the magnitude of coefficients becomes smaller for all types, and the impact on total innovation becomes insignificant. Strikingly, when a control group is restricted to runner-up municipalities in columns (5) and (6), all coefficients become insignificant indicating no significant impact of relocation on local innovation. Given this

[14]The number of municipalities where the nearest Innovation City is within $5km, 15km, 30km, 50km$ are 19, 32, 64, 94 covering 14.0%, 23.5%, 47.1%, 69.1% of municipalities of interest, respectively.

mixed and inconsistent evidence, it is difficult to state that the relocation of public agencies changes innovation in Innovation Cities and has spillover effects with confidence. However, this inconsistency is resolved when a continuous treatment variable is used.

Table 2.6 shows that the results are consistent across comparison groups when a continuous treatment variable is used to capture the magnitude and the timing of shock that each Innovation City receives more precisely. Notably, all coefficients related to total innovation, solo-work by relocated agencies, co-work by relocated agencies and local agencies are positive and significant at the one percent levels. These results imply that total innovation increases in Innovation Cities as a result of the relocation of public agencies not only due to the mechanical relocation of solo-works but also due to the increased collaboration between relocated agencies and local agencies, which indicates the existence of direct spillover effects. However, the indirect spillover effects captured by the increased innovation of local agencies are not significant.

Quantitatively, since the estimated β captures how each type of innovation changes when one potential patent relocates to Innovation Cities, the coefficients in Table 2.6 could be interpreted as *local multipliers*. Therefore, for instance, column (1) means that total innovation increases by 1.44, which is significantly larger than one considering the standard error, solo-work of relocated agencies increases by 0.92, which is significantly smaller than one considering the standard error, co-work between relocated and local agencies increases by 0.19, which is significantly larger than zero as shown, when one potential innovation relocates to Innovation Cities. Even though the relocated agencies are applying for fewer patents than before relocation in Innovation Cities, local innovation increases more than the relocated potential innovation capacity since the increase in co-works between relocated and local agencies offsets the loss of solo-works. Results in other columns are qualitatively similar and can be interpreted analogously. However, importantly, these results should not be interpreted as the aggregate innovation consequences of relocation since the relocation of public agencies must have impact on the Northwest region as well.

2.6.2 Beyond Innovation Cities

Investigating the knowledge spillover effects induced by the relocation of public agencies to Innovation Cities further, Table 2.7 shows the regression results of (2.5), which examines the spatial scope of spillovers beyond Innovation Cities. Columns (1)-(3) use the number of co-works between relocated agencies and local agencies as a dependent variable to capture the direct spillover effects, whereas columns (4)-(6) use the number of patent applications irrelevant with relocated agencies as a dependent variable to capture the indirect spillover effects of relocated agencies that accelerate local innovation. Columns (2)-(3) and (5)-(6) include the number of universities as an additional control variable, and columns (3) and (6) use province-year fixed effects instead of year fixed effects to consider province-specific time trend because all municipalities in the non-Northwest region are included in the sample now. The first row shows the knowledge spillovers within Innovation Cities, whereas the rest rows show the spillovers on municipalities by distance.

Columns (1)-(3) show that the direct knowledge spillover effects within Innovation Cities are positive and significant at the one percent level confirming the previous results in Table 2.6. Coefficients related to $5km$ are positive and significant at the one percent level indicating strong direct spillover effects beyond Innovation Cities. The coefficient for $15km$ is also significant at the five percent level in column (3). However, this spillovers beyond Innovation Cities are limited to close regions. Coefficients associated with farther municipalities are mostly not distinguishable from zero. Consistent with the null indirect spillover effects within Innovation Cities in Table 2.6, columns (4)-(6) indicate that the indirect spillovers are not observed within Innovation Cities. However, surprisingly, the impact of relocation on innovation irrelevant with relocated agencies in municipalities less than $5km$ away from Innovation Cities is positive and significant at least at the ten percent level. The coefficients for $15km$ are also significant in columns (4) and (5). Similar to the direct spillover effects, the impact of relocation dissipates away for farther municipalities, implying that indirect spillovers exist beyond Innovation Cities, but the spatial scope of spillovers is limited to very close regions.

2.6.3 Robustness check

This section investigates the robustness of the main results by (i) using different measure of knowledge spillovers; and (ii) taking logarithms. The results indicate that spillover effects within Innovation Cities are strong and robust, whereas evidence on the spillovers beyond Innovation Cities are relatively weaker.

(1) Knowledge spillovers measured with citation

Following Jaffe et al. (1993b), citation information is commonly used as a measure of knowledge spillovers. Since the citation information could capture the knowledge spillovers between relocated agencies and local agencies, the number of citations related to relocated agencies' patents (excluding self citation) is used as an alternative measure. For instance, a local agency A in municipality B applies for a patent in 2013 citing relocated agency C's patent and relocated agency D's patent, the number of citations is counted as two in municipality B in 2013. This implies that relocated agency C's knowledge is transferred to local agency A in municipality B in 2013.

Table 2.8 shows the results of estimating (2.3) using the number of citations related to relocated agencies as a dependent variable. Similar to Table 2.6, each column uses different comparison groups. The impact of relocation on the number of citations related to relocated agencies in Innovation Cities is positive and significant at the one percent level for all columns. The results are not sensitive to the choice of comparison group implying the existence of strong knowledge spillover effects of relocated agencies in Innovation Cities again. The existence of spillover effects beyond Innovation Cities and the spatial scope of spillover is shown in Table 2.9, which shows the estimation results of (2.5). Similar to Table 2.7, each column includes different control groups and different combination of fixed effects. Consistent with Table 2.8, the impact of relocation on citations related to relocated agencies within Innovation Cities is positive and significant even if spillover effects beyond Innovation Cities are considered. Only coefficients related to municipalities that are less than $15km$ away from Innovation Cities are positive and significant at the five percent level in columns (1) and (2) indicating that knowledge spillovers are limited to close regions. However, it becomes insignificant when province-year fixed effects are included, and the impact on municipalities closer than $5km$ from Innovation Cities is not distinguishable from zero. Compared to the robust impact within Innovation Cities, the spillover effects beyond Innovation Cities are relatively sensitive.

(2) Taking logarithms

Since the number of patent applications and the magnitude of shock variables IP_{mt} and $IPdistance^{d}_{mt}$ constructed from the number of patent applications vary greatly across regions, it is possible that a small number of outliers distorts the results. To mitigate this concern, logarithms are used to convert dependent variables and the shock variables. However, since those variables contain zero observations, one is added before taking logarithm. Then equation (2.3) and (2.5) are estimated to see the impact of relocation.

Table 2.10 shows qualitatively similar results. All coefficients related to total innovation, solo-work by relocated agencies, co-work between relocated agencies and local agencies are positive and significant at the one percent level regardless of comparison groups. Coefficients related to local agencies' innovation unrelated to relocated agencies are positive and significant at the ten percent level. However, they are not significant when comparison groups are restricted to other candidates or runner-ups. These results confirm that innovation increases in Innovation Cities both due to the solo-work and the co-work. There exist strong direct spillover effects of relocated agencies within Innovation Cities. Table 2.11 shows the impact of relocation on innovation within and beyond Innovation Cities. Confirming the main results in Table 2.7, the direct spillover effects in columns (1)-(3) are positive and significant at least at the five percent level within Innovation Cities and in municipalities less than $5km$ away. This effect dissipates away for farther municipalities. However, the indirect spillover effects measured by local innovation unrelated to relocated agencies are not significant even in the closest municipalities. Similar to the main results in Table 2.7, the indirect spillover effects beyond Innovation Cities seem to be weaker and inconsistent.

2.7 Conclusion

This paper examines the knowledge spillover effects caused by a quasi-experimental South Korean Innovation City project, which relocates public agencies from Seoul metropolitan area to provincial regions. The knowledge spillover effects that this project generates are explored mainly through the local innovation consequences of the relocation. South Korean patent data are classified by the relevance with relocated agencies to distinguish the mechanical increase of innovation and the knowledge spillover effects. Also, the innovation history of relocated agencies are considered to account for the heterogeneous impact that each public agency can generate to Innovation Cities more precisely. Equipped with these measures of knowledge spillovers and the shock, the impact of relocation of public agencies is explored both within Innovation Cities via a winner-loser comparison and beyond Innovation Cities using the physical distance to Innovation Cities. If knowledge spillover effects exist, it should be the strongest in Innovation Cities, and municipalities physically distant from Innovation Cities are less likely to experience the spillover of knowledge from Innovation Cities as interaction decreases in distance, for instance due to the traveling cost.

The empirical evidence shows that the relocation of public agencies increases innovation in Innovation Cities not only by the solo-work by relocated agencies, which is more mechanical, but also by the co-work between local agencies and relocated agencies, which reveals increased interactions and spillovers. However, it is not clear whether the relocation of public agencies accelerates independent innovation of local agencies through indirect spillover effect. Evidence on the spillovers beyond Innovation Cities is also found but limited to very close regions implying that knowledge spillovers are locally concentrated.

Even though this paper shows the innovation consequences that Innovation City project induced, the results should be interpreted with caution for three reasons. First, the aggregate impact is not evaluated. Since introducing public agencies increases innovation in Innovation Cities, it is likely that municipalities where public agencies depart from may experience a decrease in innovation. Whether this spatial reallocation of innovation capacity generates net gains or net losses is not answered in this paper. Second, it might be too early to evaluate the Innovation City project since the relocation of public agencies was complete in 2019, which is the last year of the sample period. It may take more years to form networks, disperse knowledge, and invent new knowledge. In addition, it is possible that educational attainment and the migration pattern change due to the decent job opportunities in Innovation Cities, which can generate the longer term impact on innovation. Third, this paper only focuses on innovation, which means no other outcome variables are explored. Evaluating the Innovation City project, even at the local level, requires analyzing its impact on many other factors including employment opportunities, housing prices, and environments to name a few. All this requires future research.

2.A Figures

Figure 2.1: Location of Innovation Cities

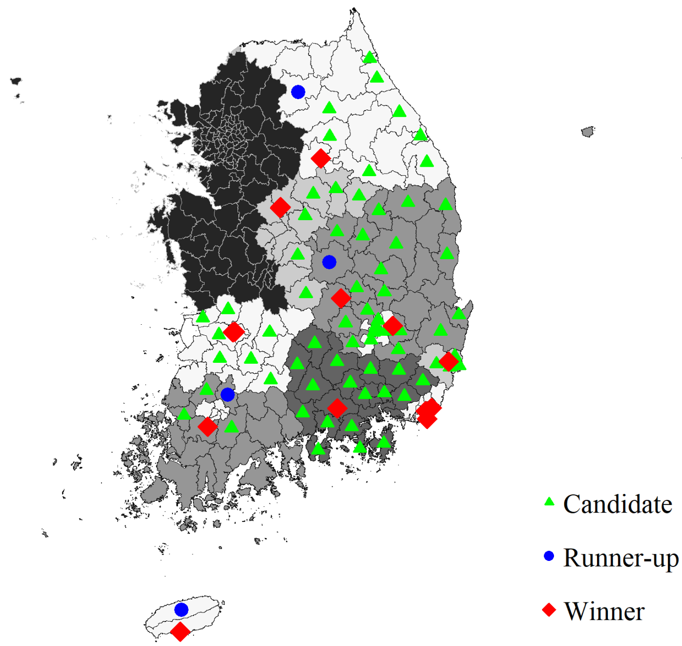


Figure 2.2: The number of patent applications

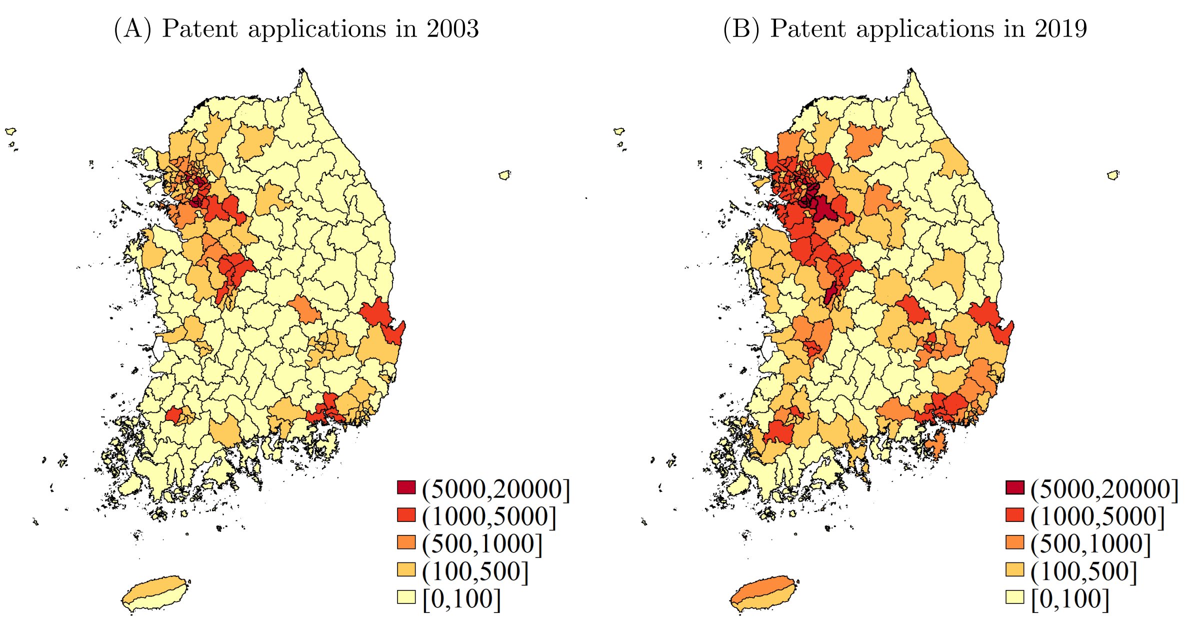


Figure 2.3: Change in the number of patent applications

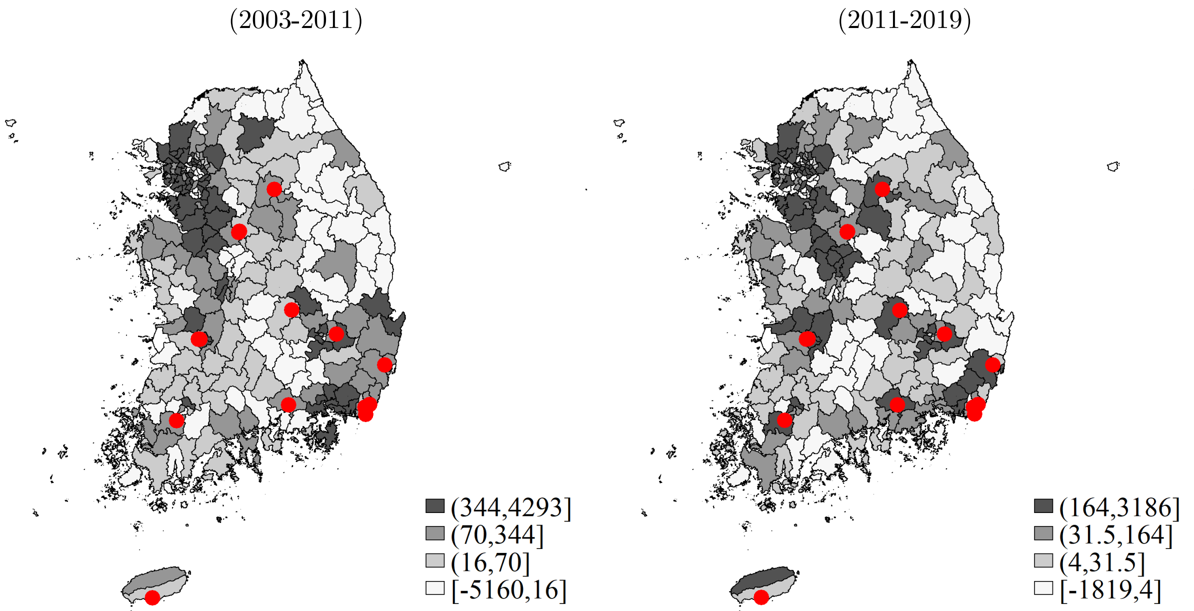
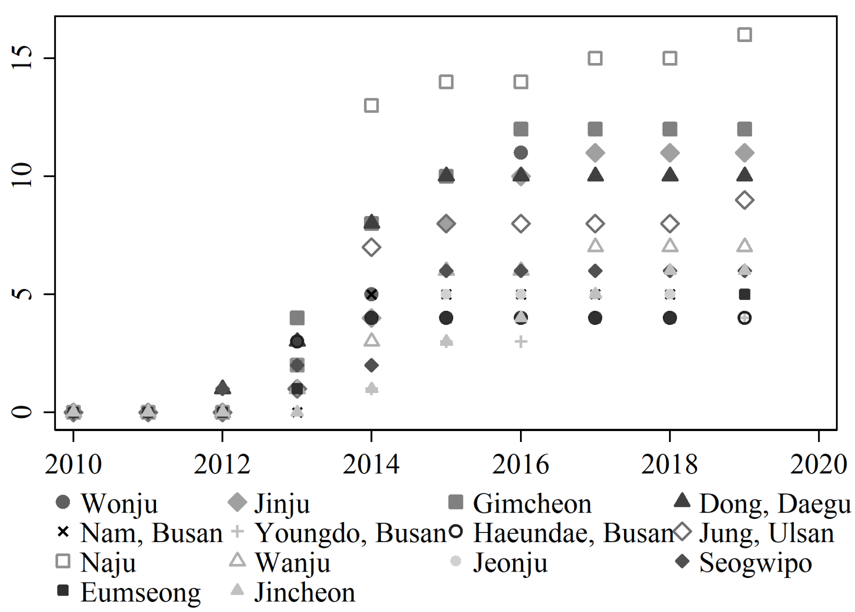
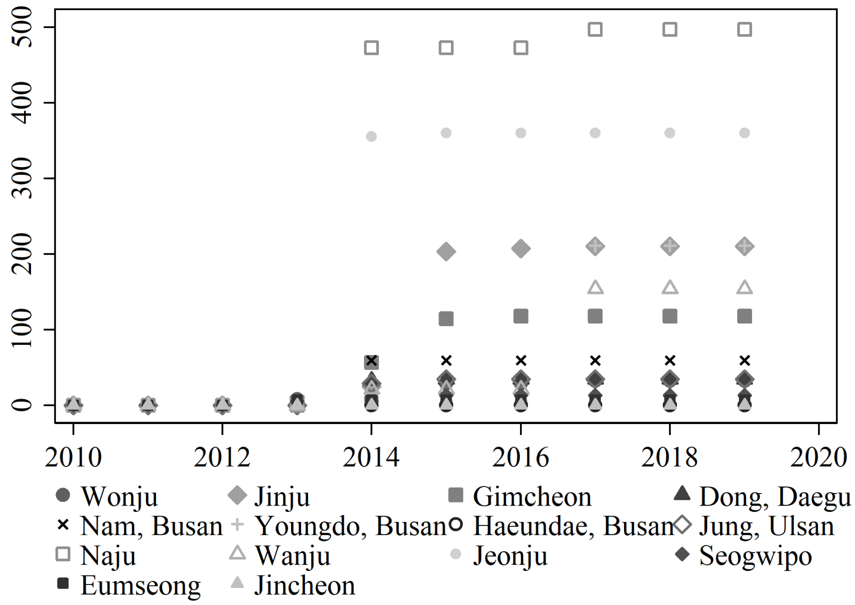


Figure 2.4: Gradual relocation of public agencies



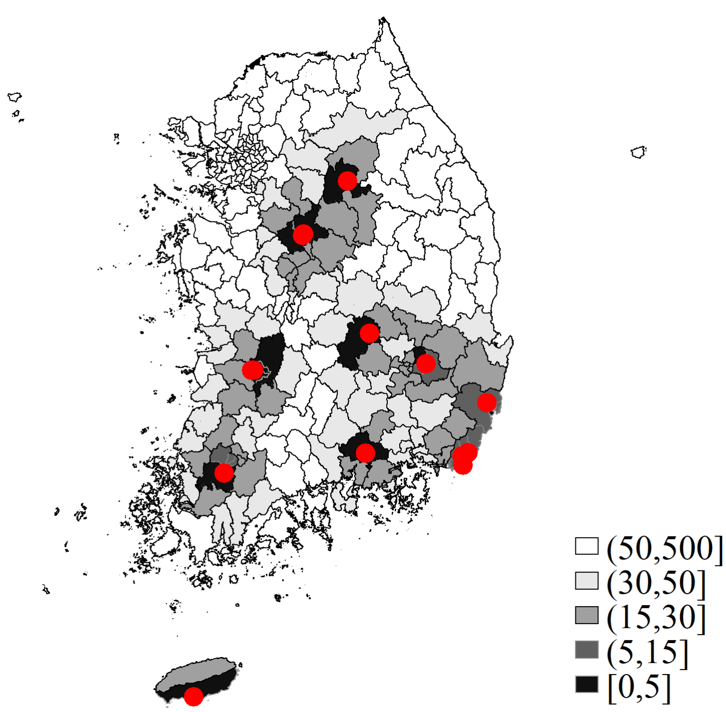
Note: The vertical axis shows the accumulated number of public agencies relocated to each Innovation City.

Figure 2.5: Time-varying treatment intensity



Note: The vertical axis shows the accumulated innovation potential to each Innovation City.

Figure 2.6: Distance to the nearest Innovation City



2.B Tables

Table 2.1: Innovation City site selection criteria

Criteria	Weight
Possibility of Development as Innovation Hub	
Proximity to transportation	20
Suitability as innovation hub	20
Availability of infrastructure and convenient facilities of the existing cities	20
Need for City Development	
Readiness and economic effect of city development	15
Environmentally-friendly development sites	10
Possibility of Shared Growth within Region	
Balanced development within region	10
Ways to share achievements of innovation city	10
Local government's support	5

Source: Guidelines on the Site Selection of Innovation City, *Ministry of land, infrastructure, and transportation.*

Table 2.2: Sector classification

Sector	KSIC 8th	KSIC 9th	KSIC 10th
Agr., fishery, and mining	A, B, C	A, B	A, B
Manufacturing	D except 22100	C	C except 34000
Construction	F	F	F
Personal services	G, H, O, P, Q, R, S	G, I, P, Q, R, S	G, I, P, Q, R, S plus 34000
Business services	I, J, K, L, M, plus 22100	H, J, K, L, M, N	H, J, K, L, M, N
Other	E, N, T	D, E, O, T, U	D, E, O, T, U

Note: Publication (22100) is reclassified as business service since it is classified as manufacturing in the 8th revision. Reparation of machinery is reclassified as personal service since it is classified as manufacturing in the 10th revision.

Table 2.3: Patenting changes by the relevance with relocated agencies

	Total (03-11)	Solo (03-11)	Co-work (03-11)	Other (03-11)	Total (11-19)	Solo (11-19)	Co-work (11-19)	Other (11-19)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	43,336	1,117	481	41,738	23,604	419	466	22,719
Northwest	26,620	1,117	420	25,083	15,024	-1,354	-144	16,522
Non-northwest	16,716	0	61	16,655	8,580	1,773	610	6,197
Candidates	13,680	0	39	13,641	6,697	1,773	588	4,336
Innovation Cities	2,248	0	7	2,241	4,330	1,773	535	2,022
Runner-ups	921	0	11	910	408	0	9	399

Note: Northwest region includes Seoul, Incheon, Kyunggi-do, Chungcheongnam-do, and Daejeon. Changes in the number of patent applications between 2003 and 2011, and 2011 and 2019 are reported in columns (1)-(4) and (5)-(8), respectively. The types of patent used are total, solo work by relocated agencies, co-work with relocated agencies, and others for columns (1) and (5), (2) and (6), (3) and (7), and (4) and (8), respectively.

Table 2.4: Municipality characteristics

	Winner	Runner-up	Candidate	Full	t stat (1)-(2)	t stat (1)-(3)	t stat (1)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of municipalities	14	4	72	122			
Patent application	210	216.7	190.2	154.8	-0.21	0.6	1.97**
change (%)	14.2	16.2	22.1	21.8	-0.42	-1.39	-1.35
Population (thousands)	237.9	206.3	156.3	141.0	1.1	4.94***	6.44***
change (%)	-0.1	-0.1	-0.5	-0.6	0.02	1.80*	2.45**
Employment (thousands)	63.4	63.5	48.8	44.5	-0.02	2.60***	3.72***
change (%)	3.1	1.9	4.3	3.6	0.58	-0.53	-0.26
MFG share	20.5	12.6	21.2	18.0	2.49**	-0.49	1.70*
change (%p)	0.2	-0.1	0.6	0.4	0.39	-0.56	-0.38
Busi. services share	16.5	16.8	12.8	13.4	-0.28	7.38***	4.73***
change (%p)	0.2	0.2	0.2	0.3	0.17	-0.07	-0.57
No. of Universities	1.4	0.8	0.6	0.5	2.40**	5.97***	7.29***
change (count)	0.03	0	0.01	0.0	0.76	1.5	1.85*

Note: Columns (1)-(4) show the mean of variables for Innovation Cities, runner-up municipalities, candidate municipalities, other non-northwest municipalities between 2003 and 2011, respectively. For the number of universities, the average between 2006 and 2011 is used, respectively. Columns (5)-(7) show the t-statistics for the mean difference between municipalities. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.5: Impact of the relocation of public agencies (DiD)

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Total	140.157*	131.205*	85.055	97.599	83.561	101.059
	(64.789)	(59.423)	(57.941)	(54.170)	(97.862)	(86.504)
Solo	74.846**	74.347**	71.353**	71.086**	63.204	60.988
	(31.216)	(30.261)	(29.408)	(27.951)	(38.745)	(39.209)
Co-work	19.261**	19.097**	18.582**	18.491**	13.394	12.617
	(6.515)	(6.353)	(6.494)	(6.341)	(7.351)	(7.210)
Others	46.050	37.761	-4.880	8.022	6.963	27.454
	(47.622)	(40.785)	(44.077)	(37.621)	(61.980)	(50.691)
# universities		✓		✓		✓
N	2312	1904	1462	1204	306	252

Note: This table shows the regression results of (2.1) using different control groups for each type of innovation. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as control variables. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.6: Impact of the relocation of public agencies (Continuous treatment variable)

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Total	1.438***	1.357***	1.316***	1.293***	1.404***	1.354***
	(0.259)	(0.209)	(0.272)	(0.232)	(0.272)	(0.207)
Solo	0.916***	0.913***	0.915***	0.909***	0.919***	0.918***
	(0.043)	(0.041)	(0.042)	(0.039)	(0.031)	(0.028)
Co-work	0.187***	0.185***	0.186***	0.184***	0.182***	0.182***
	(0.024)	(0.024)	(0.025)	(0.025)	(0.019)	(0.019)
Others	0.335	0.259	0.215	0.199	0.303	0.253
	(0.292)	(0.240)	(0.303)	(0.259)	(0.291)	(0.220)
# universities		✓		✓		✓
N	2312	1904	1462	1204	306	252

Note: This table shows the regression results of (2.6) using different control groups for each type of innovation. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as control variables. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.7: Spatial scope of knowledge spillovers

	Co-work			Local innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
1. Within Innovation Cities						
$0km$	0.177***	0.176***	0.156***	-0.338	-0.348	-0.636
	(0.029)	(0.025)	(0.031)	(0.350)	(0.307)	(0.375)
2. Beyond Innovation Cities						
$0-5km$	0.015***	0.013***	0.013***	0.320**	0.294*	0.287*
	(0.004)	(0.003)	(0.004)	(0.115)	(0.159)	(0.150)
$0-15km$	-0.003	-0.002	0.016**	0.303**	0.278*	0.550
	(0.003)	(0.003)	(0.007)	(0.125)	(0.129)	(0.343)
$0-30km$	-0.002	-0.002	-0.000	0.030	0.010	0.037
	(0.002)	(0.001)	(0.001)	(0.075)	(0.056)	(0.036)
$0-50km$	0.000	0.000	0.001	0.001	0.003	-0.017
	(0.001)	(0.001)	(0.001)	(0.057)	(0.051)	(0.042)
# universities		✓	✓		✓	✓
Municipality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	✓	
Province-year FE			✓			✓
N	2312	1904	1904	2312	1904	1904

Note: This table shows the regression results of (2.5) to show the spatial scope of knowledge spillovers for non-Northwest municipalities. Columns (1)-(3) use the number of co-work between relocated agencies and local agencies as a measure of direct knowledge spillover, whereas columns (4)-(6) use the number of local patent applications irrelevant with relocated agencies. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2)-(3), and (5)-(6) include the number of universities as control variables. All models include municipality fixed effects. Columns (3) and (6) include province-year fixed effects, whereas the rest columns include year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.8: Impact of the relocation of public agencies (citation)

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Citation related to relocated	0.119***	0.111***	0.114***	0.109***	0.111***	0.104***
	(0.009)	(0.012)	(0.010)	(0.012)	(0.012)	(0.012)
# universities		✓		✓		✓
N	2312	1904	1462	1204	306	252

Note: This table shows the regression results of (2.6) using different control groups for citations related to relocated agencies. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as control variables. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.9: Spatial scope of knowledge spillovers (citation)

	Citation between relocated and local agencies		
	(1)	(2)	(3)
1. Within Innovation Cities			
$0km$	0.095***	0.095**	0.143***
	(0.028)	(0.034)	(0.029)
2. Beyond Innovation Cities			
$0-5km$	-0.010	-0.017	-0.025
	(0.020)	(0.020)	(0.024)
$0-15km$	0.071***	0.062**	0.016
	(0.018)	(0.024)	(0.034)
$0-30km$	0.031	0.020	0.021
	(0.019)	(0.026)	(0.027)
$0-50km$	0.015	0.011	0.013
	(0.017)	(0.017)	(0.021)
# universities		✓	✓
Municipality FE	✓	✓	✓
Year FE	✓	✓	
Province-year FE			✓
N	2312	1904	1904

Note: This table shows the regression results of (2.5) to show the spatial scope of knowledge spillovers for non-Northwest municipalities using citations related to relocated agencies as a measure of spillovers. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2) and (3) include the number of universities as control variables. All models include municipality fixed effects. Columns (1) and (2) include year fixed effects, whereas columns (3) includes province-year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.10: Impact of the relocation of public agencies (logarithm)

	Full		Candidate		Runner-up	
	(1)	(2)	(3)	(4)	(5)	(6)
Total	0.111***	0.108***	0.106***	0.100***	0.110***	0.110***
	(0.018)	(0.019)	(0.023)	(0.021)	(0.033)	(0.027)
Solo	0.918***	0.919***	0.915***	0.917***	0.924***	0.928***
	(0.048)	(0.042)	(0.049)	(0.041)	(0.031)	(0.028)
Co-work	0.535***	0.533***	0.528***	0.532***	0.517***	0.516***
	(0.042)	(0.043)	(0.045)	(0.044)	(0.049)	(0.045)
Others	0.029*	0.026*	0.025	0.018	0.019	0.019
	(0.014)	(0.012)	(0.014)	(0.014)	(0.018)	(0.013)
# universities		✓		✓		✓
N	2312	1904	1462	1204	306	252

Note: This table shows the regression results of (2.6) using different control groups for each type of innovation. Columns (1)-(2) use all other non-Northwest municipalities, whereas columns (3)-(4) and (5)-(6) use all non-winning candidate municipalities and runner-up municipalities as control groups, respectively. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2), (4), and (6) include the number of universities as control variables. All models include municipality fixed effects and year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table 2.11: Spatial scope of knowledge spillovers (logarithm)

	Co-work			Local innovation		
	(1)	(2)	(3)	(4)	(5)	(6)
1. Within Innovation Cities						
$0km$	0.497***	0.486***	0.537***	0.020	0.011	0.033
	(0.042)	(0.043)	(0.032)	(0.016)	(0.012)	(0.028)
2. Beyond Innovation Cities						
$0-5km$	0.022*	0.037***	0.029**	-0.016	-0.018	-0.027
	(0.011)	(0.006)	(0.010)	(0.033)	(0.037)	(0.047)
$0-15km$	0.026	0.018	-0.031	0.028	0.033	0.010
	(0.019)	(0.020)	(0.033)	(0.034)	(0.037)	(0.026)
$0-30km$	-0.021	-0.019	-0.021*	-0.004	0.001	0.008
	(0.014)	(0.011)	(0.011)	(0.010)	(0.013)	(0.016)
$0-50km$	0.018	0.015	0.016	0.009	0.007	-0.001
	(0.012)	(0.012)	(0.016)	(0.017)	(0.014)	(0.020)
# universities		✓	✓		✓	✓
Municipality FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓		✓	✓	
Province-year FE			✓			✓
N	2312	1904	1904	2312	1904	1904

Note: This table shows the regression results of (2.5) to show the spatial scope of knowledge spillovers for non-Northwest municipalities. Columns (1)-(3) use the number of co-work between relocated agencies and local agencies as a measure of direct knowledge spillover, whereas columns (4)-(6) use the number of local patent applications irrelevant with relocated agencies. All columns include population and employment in logarithm, employment share of manufacturing, and employment share of business services as control variables. In addition, columns (2)-(3), and (5)-(6) include the number of universities as control variables. All models include municipality fixed effects. Columns (3) and (6) include province-year fixed effects, whereas the rest columns include year fixed effects. Standard errors in parenthesis are clustered by province. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Chapter 3

Labor Share in General Equilibrium

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3.1 Introduction

The stability of the labor share in GDP was one of the most famous "stylized facts" of growth (Kaldor, 1961). However, there is a consensus that the fall in the labor share of GDP in recent decades is significant not only in the United States (Elsby et al., 2013), but also in other countries around the world (Dao et al., 2017). Nevertheless, the reason for the decline is still in controversy, despite there are candidates including labor-capital substitution (Karabarbounis and Neiman, 2014), labor-displacing automation (Acemoglu and Restrepo, 2020; Autor and Salomons, 2018), the rise of superstar firms (Autor et al., 2020b), stronger market power (Gutierrez and Phillipon, 2017; De Loecker et al., 2020; Macedoni, 2022), global integration (Elsby et al., 2013; Dao et al., 2017; Xu et al., 2018), and tax in favor of capital and wealth (Piketty, 2014; Smith et al., 2021). To explore this question deeper, we develop a Melitz model with ex-ante identical individuals who choose to be entrepreneurs or workers. This model shows that the change in fiscal policies influences the labor share not only through the direct redistribution, but also through this occupational choice in general equilibrium. Specifically, our model suggests that corporate-friendly fiscal policy decreases the labor share, but the decrease is partly offset by an increase in competition between entrepreneurs induced by new entry.

The first building block of the model is the free occupational choice of individuals as in Lucas (1978). Individuals are ex-ante identical and can freely choose to be either an entrepreneur or a worker. An entrepreneur earns profits by running her own firm hiring who choose to be workers. It is assumed that identical workers are mobile across firms so that all workers earn the same wages. We normalize wage to one considering labor as a numeraire. However, unlike the identical workers, entrepreneurs are ex-post heterogeneous due to the next ingredient.

The second building block of the model is the heterogeneous productivity of entrepreneurs as in Melitz (2003). Entrepreneurs draw their productivity upon entry from a known distribution and earn heterogeneous profits based on their productivity draw. Entrepreneurs with high productivity make large profits, whereas entrepreneurs with low productivity may earn less than their employees. Entrepreneurs with productivity lower than a cutoff productivity decide not to operate since they cannot earn positive profits. Knowing this heterogeneity, ex-ante identical individuals choose their occupation comparing the expected income of an entrepreneur and a worker. Therefore, through the free occupation choice, the expected income of two occupations becomes the same in equilibrium, and the fraction of entrepreneurs and workers are endogeneously determined. Importantly, this *free entry condition* sheds light on the entry cost in Melitz-type model, which justifies the positive profits of firms, although it is not clear whether firms really pay the entry cost in reality. In contrast, our model implies that entrepreneurs are paying the opportunity cost as the entry cost by giving up wages. This clearly answers what the entry cost is, and whether entrepreneurs pay the cost.

The third building block of the model is the demand structure that corresponds to the non-constant markup that entrepreneurs charge. Specifically, the quadratic mean of order 2 (QMO2) expenditure function is used to represent consumer preferences following Feenstra (2018b). The QMO2 expenditure function implies an increasing elasticity of demand in price (Marshall's second law of demand) and increasing markups of entrepreneurs in productivity. As a result, the firm-level labor share is heterogeneous across firms, which allows us to examine richer channels through which the labor share responds to fiscal policies.

The fourth building block of the model is the government expenditure, tax, and redistribution. It is assumed that the government spends a fixed proportion of total output for its purpose and redistributes the rest of the tax revenues so that the fiscal balance is achieved. No specific tax structure is assumed, but the tax scheme on wage income and entrepreneur income can be different as in reality. As a result, individuals consider not only the gross income but also the tax burden in choosing their occupation. Therefore, fiscal policies affect the labor share not only through the direct redistribution, but also through the occupational choice in general equilibrium by changing the net income of workers and entrepreneurs.

Armed with these components, assuming the bounded Pareto distribution of productivity as in Feenstra (2018b), we compare the equilibrium labor share under rigid entry adjustment and flexible entry adjustment to explore the impact of fiscal policy. It is shown that corporate-friendly fiscal policy directly decreases the labor share by redistributing income from workers to entrepreneurs. However, when this policy attracts more individuals to be entrepreneurs, resource allocation changes in two ways. First, stronger competition forces entrepreneurs to charge lower markups, which increases the firm-level labor share. Second, as competition strengthens, low-productivity entrepreneurs exit the market and resources are reallocated to more productive firms whose labor shares are lower, which decreases the average labor share. Since the former within-firm-reallocation force is stronger than the latter between-firm-reallocation when bounded Pareto distribution is assumed, this general equilibrium effect partly offsets the initial direct decrease of the labor share. In contrast, in the absence of this entry adjustment, the labor share declines more than it should do due to the lack of competition induced by new entrants.

Our model is closely related to Autor et al. (2020b), which adds to the debate on the role of competition on concentration and the labor share. For instance, Gutierrez and Phillipon (2017) show that competition decreases in the United States, which leads to the increase in concentration and the labor share decreases more in industries that have become more concentrated. In contrast, Autor et al. (2020b) focus more on the rise of competition. More specifically, their model of superstar firms is characterized by heterogeneous firms under monopolistic competition and demand structure satisfying Marshall's second law of demand, which implies that larger firms have lower labor shares as in our model. Then, more intense competition leads to an increase in the firm-level labor share as each firm charges lower markups, whereas tougher competition reallocates resources toward firms with lower labor shares at the same time. This is exactly what happens in general equilibrium as a result of the entry adjustment in our model except that the source of competition and the entry adjustment is not explicitly considered in their model. The authors show that the latter between-firm reallocation dominates the former within-firm reallocation when the probability density function (pdf) of productivity is log-convex, whereas the within-firm reallocation dominates when the pdf is log-concave, and two forces cancel out each other when the pdf is log-linear. Importantly, Pareto distribution, which is commonly used to represent the distribution of productivity in heterogeneous firm models, has a log-linear density function, which is the reason why stronger competition does not change the factor share in Melitz and Ottaviano (2008) type model imposing a Pareto assumption.

Our model complements Autor et al. (2020b) in multiple ways. First, we highlight the importance of initial force that induces tougher competition by showing that the corporate-friendly fiscal policy decreases the labor share even if entry adjustment is rigid and therefore the level of competition does not change. Since this direct impact of policy on the labor share could be more important than the change in the labor share followed by the general equilibrium effect, more attention should be paid to the source of the decline in the labor share. Importantly, this margin of impact becomes explicit by considering the occupational choice of individuals. Second, we echo these authors in that Pareto distribution veils the general equilibrium effect. As the between-firm reallocation completely offsets the change of labor share induced by the within-firm reallocation under unbounded Pareto distribution, the general equilibrium effect induced by the occupational choice of individuals is muted. In addition, by showing that the general equilibrium effect exists under bounded Pareto distribution, whose pdf is also log-linear, the Marshall's second law of demand and the log-convexity of probability density are not sufficient for tougher competition to decrease the labor share when the entry/exit adjustment or the occupational choice is considered.

The remaining part is organized as follows. Section 3.2 develops a model to provide a framework. Section 3.3 examines the labor share implications of the corporate-friendly fiscal policy. Section 3.4 explores this question through a parametric example using bounded Pareto distribution. Section 3.5 concludes.

3.2 Model

3.2.1 Environment

Each member of the unit mass of population chooses to be either a worker or an entrepreneur. We denote the mass of workers as M_w and the mass of entrepreneurs as M_e, which sum to one. A worker inelastically supplies labor to earn the normalized wage of one, whereas an entrepreneur draws productivity from a known distribution upon entry and hires workers to make profit π. Government imposes income tax, purchases an exogenous fraction of the total output for its purposes, and redistributes the rest. Tax rate depends on the type of income so that the net income of a worker and an entrepreneur becomes $\tau_w(1)$ and $\tau_e(\pi)$, respectively.[1]

3.2.2 Consumer problem

Preferences are represented by the symmetric case of quadratic mean of order two (QMO2) expenditure function adopting Feenstra (2018b). The QMO2 function over a continuum of goods indexed by ω with price vector $\mathbf{p}$ is

$$e(\mathbf{p}) = \left[\alpha \int p_\omega^2 d\omega + \beta \left(\int p_\omega d\omega\right)^2\right]^{1/2} \quad \text{where } \alpha < 0\,,\ \beta > 0, \tag{3.1}$$

which indicates the minimum expenditure to obtain one unit of utility, or the cost of living. One of the advantages that QMO2 expenditure function has over commonly used constant elasticity of substitution (CES) preferences is that there exists a finite reservation price p^*, where demand is positive if and only if price is less than p^*. Appendix B.1 shows that the reservation price can be derived as

$$p^* = \frac{\int_\Omega p_\omega d\omega}{N - \tilde{N} - \alpha/\beta}, \tag{3.2}$$

where $\Omega \equiv \{\omega | p_\omega < p^*\}$ is the set of available goods, $N \equiv \int_\Omega d\omega$ is the mass of available goods, and $\tilde{N} \equiv \int d\omega$ is the mass of all possible goods. It is assumed that $0 < \tilde{N} + (\alpha/\beta) < N$. Using this, Appendix B.1 also shows that the demand function of consumer i with net income $\tau_i(y_i)$ for variety ω with price p_ω is

$$D_i(p_\omega) = \alpha (p_\omega - p^*)\, e(\mathbf{p})^{-2} \tau_i(y_i), \tag{3.3}$$

where $D_i(p_\omega) = 0$ for all $p_\omega \geq p^*$ by definition of p^*. Note that the reservation price is symmetric for all consumers with different income due to the homotheticity implied by the QMO2 expenditure function. Another advantage this demand structure exhibits is that it satisfies Marshall's second law of demand, which implies non-constant markups that entrepreneurs charge. More specifically, the price elasticity of demand is increasing in price since $-\frac{\partial ln D_i(p_\omega)}{\partial ln(p_\omega)} = \frac{p_\omega}{p^* - p_\omega}$. Therefore, entrepreneurs who can set low prices face low elasticity, which allows them to charge high markups. This indicates that the reallocation of resources between firms with different markups could have labor share

[1] $\tau_w(1)$ and $\tau_e(\pi)$ can be understood as $1-$wage tax and $\pi-$profit tax, respectively.

consequences as shown in Section 3.3.

3.2.3 Entrepreneur problem

An entrepreneur draws productivity ϕ upon entry from a known distribution. The entrepreneur uses labor ℓ as the only input and has a production function $x(\phi) = \phi\ell$. Since wage is normalized to unity, this is equivalent to drawing marginal cost $c = 1/\phi$, which is the amount of labor required to produce one unit of output. Considering this, we assume that an entrepreneur draws marginal cost c from a distribution $F(c)$. Note that the total demand for a good with price p_ω is

$$\int_i \alpha \left(p_\omega - p^*\right) e\left(\mathbf{p}\right)^{-2} \tau_i \left(y_i\right) di + \alpha \left(p_\omega - p^*\right) e\left(\mathbf{p}\right)^{-2} G \tag{3.4}$$

where the first component is the sum of private consumption and the second component indicates government consumption. It is assumed that the demand function of the government has the same structure as consumers except that it spends G. Considering this demand, an entrepreneur with c solves

$$\underset{p}{Max}(p-c)\alpha(p-p^*)e(\mathbf{p})^{-2}Y, \tag{3.5}$$

where $Y \equiv \int_i \tau_i(y_i)di+G$ is the total expenditure of the economy. As a result, the profit maximizing price and quantity can be derived as

$$p(c;p^*) = \frac{p^*+c}{2}, \quad q(c;p^*) = -\frac{p^*-c}{2}\alpha e(\mathbf{p})^{-2}Y, \tag{3.6}$$

which yields the maximized profits of an entrepreneur with c as

$$\pi(c;p^*) = -\frac{(p^*-c)^2}{4}\alpha e(\mathbf{p})^{-2}Y. \tag{3.7}$$

3.2.4 Equilibrium

Following Melitz (2003) type heterogeneous firm models, we combine relevant equilibrium conditions to find the equilibrium of the model. As a starting point, prior to investigating the conditions, it is useful to define the zero profit cutoff cost $\bar{c}$ and to re-express the expenditure function $e(\mathbf{p})$ using it since they greatly simplify the equilibrium conditions. First, the optimal price choice of an entrepreneur with c and corresponding demand implies that the zero profit cutoff cost should be $\bar{c} = p^*$ so that $\pi(c; p^*) = 0$ for all $c \geq \bar{c}$. Second, considering the optimal prices of entrepreneurs, Appendix B.2 shows that the expenditure function can be simplified as

$$e(\mathbf{p})^2 = -\frac{\alpha}{4} M_e \int_{c<p^*} (p^{*2} - c^2) dF(c) \tag{3.8}$$

(1) Fiscal balance condition

The first equilibrium condition is the fiscal balance condition (FB), which means that total tax revenues should be equal to government expenditures. Formally, we can write the condition as

$$M_w (1 - \tau_w(1)) + M_e \int \big(\pi(c) - \tau_e(\pi(c))\big) dF(c) = G, \tag{3.9}$$

where the left hand side stands for tax revenues, since the first term is the revenues from workers, and the second term is the revenues from entrepreneurs. We assume the government expenditures G are the exogenous fraction of total output ($G = gY$).

(2) Labor market equilibrium condition

The second equilibrium condition is the labor market equilibrium condition (LME) or the full employment condition, which means that the supply of workers should be equal to the workers hired by entrepreneurs. Formally, this condition is written as

$$M_w = M_e \int_{c<p^*} c q(c) dF(c). \tag{3.10}$$

Since all workers supply one unit of labor inelastically, M_w stands for the total workers supplied. The right hand side stands for the workers hired for production since it implies that among M_e entrepreneurs, those with $c < p^*$ produce $q(c)$ units of output hiring c workers for each unit. Using $q(c)$ and $e(\mathbf{p})$ from (3.6) and (3.8), this condition simplifies to

$$M_w = A(p^*) Y \text{ , where } A(p^*) \equiv \frac{2 \int_{c<p^*} \left(p^* c - c^2\right) dF(c)}{\int_{c<p^*} (p^{*2} - c^2) dF(c)}. \tag{3.11}$$

(3) Free entry condition

Since individuals can freely choose their occupation, they become workers as long as the net wage is greater than the net expected profit, and they become entrepreneurs when the net expected profit is larger than the net wage. Therefore, in equilibrium, the net wage should be equal to the net expected profit. The third equilibrium condition of our model, the free entry condition (FE), stands for this relationship. This condition implies that an entrepreneur is paying the opportunity cost as the entry cost, which answers what entry cost is, and whether firms really pay the cost in Melitz (2003) style models. In our model, an entrepreneur clearly gives up the expected income of being a wage worker. Formally, this condition is written as

$$\tau_w(1) = \int \tau_e\left(\pi\left(c\right)\right) dF\left(c\right). \tag{3.12}$$

The left hand side indicates the net income of a wage worker, which is identical across all workers, whereas the right hand side stands for the expected net profit of an entrepreneur.

(4) Entry equation

Combining three equilibrium conditions, we can derive the following equation as shown in Appendix B.3, which is one of the two equations that characterize the equilibrium:

$$M_e = 1 - \frac{\tau_w\left(1\right)}{1-g} \times A(p^*). \tag{3.13}$$

Importantly, all three equilibrium conditions are used to derive this equation. Therefore, this equation shows the relationship between p^* and M_e in equilibrium. More specifically, since all three conditions take p^* as given, this equation shows how M_e is determined for a given p^*. Considering this, we name this equation the entry equation.

(5) Reservation price equation

To close the model, we need another equation that shows how p^* is determined for a given M_e.

Recall that the reservation price can be written as

$$p^* = \frac{\int_\Omega p_\omega d\omega}{N - \tilde{N} - \alpha/\beta}. \tag{3.14}$$

Replacing $\int_\Omega p_\omega d\omega$ with $M_e \int_{c<p^*} \frac{p^*+c}{2} dF(c)$ using (3.6), and substituting N with $M_e F(p^*)$ using $\bar{c} = p^*$, this equation becomes

$$M_e \big(p^* F(p^*) - \int_{c<p^*} \frac{p^*+c}{2} dF(c)\big) = p^* \left(\tilde{N} + \frac{\alpha}{\beta}\right), \tag{3.15}$$

which simplifies to

$$M_e = \frac{p^* \left(\tilde{N} + \frac{\alpha}{\beta}\right)}{\int_{c<p^*} \frac{p^*-c}{2} dF(c)}. \tag{3.16}$$

Since this equation implicitly determines the level of reservation price p^* for a given M_e, we name this equation the reservation price equation. Since there are two unknowns p^*, M_e, the entry equation and the reservation price equation determine the equilibrium.

(6) Equilibrium labor share

Since there are only two types of income in our model, wage and profit, we define the labor share as a counter part of the profit share. In other words, the labor share is the share of worker's net income in total net income.[2] Formally, the labor share S_L is defined as

$$S_L = \frac{M_w \tau_w(1)}{(1-g)Y}.$$

Using the labor market equilibrium condition (3.11), this becomes

$$S_L = \frac{A(p^*)\tau_w(1)}{1-g}. \tag{3.17}$$

This expression shows that the labor share depends not only on the exogenous fiscal policy variables $\tau_w(1)$ and g, but also on the equilibrium p^*, which induces the general equilibrium effect.

[2] We focus on the private sector since we focus on the distribution between workers and entrepreneurs rather than between private and public sector.

3.3 Policy Analysis: corporate-friendly fiscal policy

We examine the labor share consequences of fiscal policy under two conditions: rigid entry adjustment and flexible entry adjustment. When the entry adjustment is rigid, M_e and M_w are assumed to be fixed. In this equilibrium, the fiscal balance condition and the labor market condition are satisfied, whereas the free entry condition can be violated. However, when the entry adjustment is flexible, this violation leads M_e and M_w to change so that the free entry condition holds as well. We interpret the labor share change under rigid entry adjustment as a direct effect through redistribution, whereas the additional labor share change under flexible entry adjustment as a general equilibrium effect.

The government is constrained by the fiscal balance condition (3.9). Therefore, we focus on the change in g and $\tau_w(1)$ since the fiscal balance condition automatically determines $\int \tau_e(\pi(c))dF(c)$. Note that the reservation price (3.2) implies that p^* does not change when M_e is fixed. As a result, $e(\mathbf{p})$ does not change as is shown in (3.8), Y remains the same as can be seen from (3.11), and therefore $\int \pi(c)dF(c)$ is fixed. Therefore, noting that the labor share is $S_L = \frac{A(p^*)\tau_w(1)}{1-g}$, the direct effect of fiscal policy depends on the relative change in g and $\tau_w(1)$ as follows:

$$dS_L|_{rigid} = A(p^*) \times d\left(\frac{\tau_w(1)}{1-g}\right). \tag{3.18}$$

Since p^* does not change when the entry adjustment is rigid, the labor share changes only through the change in $\frac{\tau_w(1)}{1-g}$. To examine this result further, we define the level of $d\tau_w(1)$ corresponding to the change in g that keeps the labor share fixed as $d\tau_w^{cut}$ under rigid entry adjustment. More specifically, we have

$$\frac{\tau_w(1)}{1-g} = \frac{\tau_w(1) + d\tau_w^{cut}}{1-(g+dg)}. \tag{3.19}$$

By rearranging this, we get

$$d\tau_w^{cut} = -\frac{\tau_w(1)}{1-g}dg. \tag{3.20}$$

Then modifying this with $dg = -d\,(1-g)$, we get

$$d\tau_w^{cut} = \frac{\tau_w(1)}{1-g}d\,(1-g)\,, \tag{3.21}$$

which is equivalent to

$$\frac{d\tau_w^{cut}}{\tau_w(1)} = \frac{d\,(1-g)}{1-g}. \tag{3.22}$$

Therefore, when the rate of change in $\tau_w(1)$ is exactly the same as that of $1-g$, the labor share remains unchanged. The change in $\tau_w(1)$ should be *elastic* to the change in $1-g$ for the labor share to incline. Therefore, the labor share declines when the change in fiscal policy meets the following condition:

$$\frac{d\tau_w(1)}{\tau_w(1)} < \frac{d\,(1-g)}{1-g}. \tag{3.23}$$

For instance, assume that the government decreases $\tau_w(1)$ keeping g fixed, and therefore (3.23) holds. The fiscal balance condition implies that the net profits of entrepreneurs increase as a result of this corporate-friendly tax reform, and the labor share falls. Instead, suppose g falls, and the government collects less tax from both workers and entrepreneurs. In this case, even if the net income of workers increases, the labor share can fall when (3.23) holds since the tax cut mostly accrues to entrepreneurs. Therefore, we interpret the corporate-friendly fiscal policy as the policy change that meets (3.23).

Moreover, as a result of the change in fiscal policy, the free entry condition may be violated, which gives rise to the entry adjustment until the expected net income of a worker and an entrepreneur becomes equal. In consequence, the equilibrium M_e and p^* can be affected. Considering this entry effect, the labor share change due to the fiscal policy is

$$dS_L|_{flexible} = A(p^*) \times d\left(\frac{\tau_w(1)}{1-g}\right) + \underbrace{A'(p^*) \times \frac{\partial p^*}{\partial \frac{\tau_w(1)}{1-g}} \times d\left(\frac{\tau_w(1)}{1-g}\right) \times \frac{\tau_w(1)}{1-g}}_{General\ equilibrium\ effect} \tag{3.24}$$

where $A(p^*) \times d\left(\frac{\tau_w(1)}{1-g}\right)$ is the direct effect, and the rest terms indicate the general equilibrium effect, which occurs through the change in p^* and $A(p^*)$. Depending on the sign of $A'(p^*)$ and $\frac{\partial p^*}{\partial \frac{\tau_w(1)}{1-g}}$, the direct effect of the fiscal policy can be accelerated or offset by the general equilibrium effect.

3.4 Parametric Example: Bounded Pareto Distribution

In this chapter, we take an example of the bounded Pareto distribution of productivity, which corresponds to $F(c) = \frac{c^\theta - b^\theta}{a^\theta - b^\theta}$ with $c \in [b, a]$[3] slightly modifying Feenstra (2018b) to illustrate the labor share consequence of the corporate-friendly fiscal policy.

3.4.1 Equilibrium under bounded Pareto distribution

The entry equation (3.13) under bounded Pareto distribution is

$$M_e = 1 - \frac{\tau_w(1)}{1-g} \times \underbrace{\frac{2\theta p^{*\theta+2} - 2\theta(\theta+2)p^* b^{\theta+1} + 2\theta(\theta+1)b^{\theta+2}}{2(\theta+1)p^{*\theta+2} - (\theta+1)(\theta+2)p^{*2}b^\theta + \theta(\theta+1)b^{\theta+2}}}_{A(p^*)\ under\ bounded\ Pareto}, \tag{3.25}$$

where the last term is the expanded form of $A(p^*)$ under bounded Pareto distribution. Similarly, the reservation price equation (3.16) is

$$M_e = \frac{2p^*\left(a^\theta - b^\theta\right)(\theta+1)\,(\tilde{N} + \alpha/\beta)}{p^{*\theta+1} - (\theta+1)\,p^* b^\theta + \theta b^{\theta+1}}. \tag{3.26}$$

Using these two equations, we can find the equilibrium M_e and p^*, which determines the labor share in equilibrium. The left panel of Figure 3.1 shows how these two equations determine the equilibrium.[4] Two endogenous variables p^* and M_e are assigned to horizontal axis and vertical axis, respectively. The blue curve stands for the reservation price equation, and the red curve stands for the entry equation. Two points are noteworthy. First, the reservation price curve is downward-sloping, which implies that p^* falls when M_e increases. This reveals the "competition" effect induced by the increase in M_e. As more entrepreneurs enter the market, the product space becomes crowded, and the cutoff marginal cost (which is equivalent to p^*) becomes smaller. Second, the entry curve is upward-sloping, which implies that M_e increases when p^* increases. This result is obtained since $A'(p^*) < 0$ when bounded Pareto distribution is assumed. It is an intuitive result since an increase in p^* implies a higher probability to survive upon entry, which makes being an entrepreneur more attractive. We prove the slope of two curves in Appendix B.4.

[3]Drawing productivity ϕ from the bounded Pareto distribution $G(\phi) = \frac{a^\theta - \phi^{-\theta}}{a^\theta - b^\theta}$ where $\phi \in [a^{-1}, b^{-1}]$ and $a > b > 0$ is equivalent to drawing marginal cost c from $F(c)$ where $c \in [b, a]$ since $c = 1/\phi$

[4]The range of p^* in the graph is limited to the area such that reservation price is defined for $M_e \in [0, 1]$

Finally, the labor share (3.17) under bounded Pareto distribution is

$$S_L = \frac{\tau_w\,(1)}{1-g} \times \underbrace{\frac{2\theta {p^*}^{\theta+2} - 2\theta\,(\theta+2)\,p^* b^{\theta+1} + 2\theta\,(\theta+1)\,b^{\theta+2}}{2(\theta+1){p^*}^{\theta+2} - (\theta+1)\,(\theta+2)\,{p^*}^2\ b^{\theta} + \theta\,(\theta+1)\,b^{\theta+2}}}_{A(p^*)\ under\ bounded\ Pareto}, \tag{3.27}$$

where the last term is the expanded form of $A(p^*)$ under bounded Pareto distribution. The right panel of Figure 3.1 shows that the labor share is determined automatically as a function of the equilibrium p^*. The labor share curve is downward sloping because a decrease in p^* has two effects on the labor share. First, it decreases the markup each firm charges, which increases the firm-level labor share. More formally, the firm-level labor share $s_l(c;p^*)$ is

$$s_l(c;p^*) = 1 - \frac{\pi(c;p^*)}{p(c;p^*)q(c;p^*)} = \frac{2c}{p^*+c}, \tag{3.28}$$

which is decreasing in p^*. Therefore, a decrease in p^* results in the within-firm reallocation of income from entrepreneurs to workers. Second, noting that $s_l(c;p^*)$ is increasing in c, a decrease in the cutoff marginal cost p^* implies the between-firm reallocation of resources toward low marginal cost firms whose labor shares are also low. In other words, as firms with the highest labor shares exit the market due to the tougher competition, the average labor share of survivors falls. The former within-firm reallocation dominates the latter between-firm reallocation when bounded Pareto distribution is assumed.

When unbounded Pareto distribution is assumed instead, $A(p^*)$ becomes a constant $\frac{\theta}{\theta+1}$ since $b=0$. Therefore, the entry equation becomes a horizontal line as in the left panel of Figure **??**, which does not depend on the level of p^*:

$$M_e = 1 - \frac{\tau_w(1)}{1-g} \times \frac{\theta}{\theta+1}. \tag{3.29}$$

The reservation price equation also changes to

$$M_e = \frac{2a^{\theta}\,(\theta+1)\,(\tilde{N}+\alpha/\beta)}{{p^*}^{\theta}}, \tag{3.30}$$

which is represented by a downward sloping curve as in the left panel of Figure **??**. The equilibrium is determined at the intersection of two curves. Also, the labor share curve becomes a horizontal line independent of p^* as in the right panel of Figure ??:

$$S_L = \frac{\theta}{\theta + 1} \times \frac{\tau_w(1)}{1-g}. \tag{3.31}$$

Therefore, the within-firm reallocation induced by the change in p^* is completely offset by the between-firm reallocation when unbounded Pareto distribution is assumed.

3.4.2 Corporate-friendly fiscal policy under bounded Pareto distribution

Figure 3.2 illustrates the labor share consequence of corporate-friendly fiscal policy. (3.17) implies that the labor share curve shifts downward following the corporate-friendly policy as shown in the left panel. Noting that p^* does not change when the entry adjustment is rigid, this downward shift of the labor share curve is the only source that affects the labor share. As a result, the equilibrium changes from E_0 to E_r, and the labor share falls as shown in the left panel. The direct effect of the corporate-friendly tax policy decreases the labor share through redistribution.

However, this tax reform leads to the violation of the free entry condition since the expected net income of an entrepreneur becomes higher than the net income of a worker. Therefore, when M_e is flexible, the corporate-friendly tax reform shifts the entry curve upward as shown in the right panel. As a result, the equilibrium changes to E_f, and the equilibrium p^* decreases as shown in the right panel. In other words, since more individuals choose to be entrepreneurs following the corporate-friendly fiscal policy, the product space becomes crowded, which makes competition more intense (smaller p^*). To deal with the competition, each firm charges lower markup, which increases the firm-level labor share. As a result, the labor share increases along the new labor share curve as shown in the left panel. In consequence, this general equilibrium effect, which occurs through the entry adjustment, offsets the direct effect of the corporate-friendly fiscal policy. Mathematically speaking using (3.24), the general equilibrium effect offsets the direct effect since $\frac{\partial p^*}{\partial \frac{\tau_w(1)}{1-g}} > 0$ and $A'(p^*) < 0$ under bounded Pareto distribution.

How large is this general equilibrium effect? It can be shown that this general equilibrium effect does not overturn the direct effect. To prove this, we show that the sign of net effect is the same as the direct effect. Note that when M_e is flexible, the free entry condition implies

$(1-g)Y = M_w \tau_w(1) + M_e \tau_w(1)$, and therefore, $S_L = M_w$. In other words, the labor share declines as long as M_w falls or M_e increases when entry adjustment is flexible. As Figure 3.2 shows, since the entry curve shifts upward and the equilibrium M_e increases, the labor share falls in net. Therefore, the direct effect of is only partly offset by the general equilibrium effect.

The mirror image of this result, which is more interesting, is that the labor share declines more than it should do when the entry adjustment is rigid. The labor share over-responds to the corporate-friendly fiscal policy in the absence of more entry of entrepreneurs because the labor share stabilizing competition effect is absent.

When unbounded Pareto distribution is assumed instead, the labor share is independent of p^* as in (3.31). Therefore, the general equilibrium effect through p^* does not exist and the direct redistribution through the change in $\frac{\tau_w(1)}{1-g}$ explains the entire change in the labor share. Figure 3.4 illustrates this result. Since the corporate friendly fiscal policy redistributes income between workers and entrepreneurs, the labor share curve shifts downward regardless of the entry adjustment. Since this policy change makes entrepreneur more attractive, the entry curve shifts upward and the equilibrium reservation price falls revealing tougher competition between entrepreneurs. However, unlike the bounded Pareto case, this change in p^* does not affect the equilibrium labor share as within-firm reallocation and between-firm reallocation cancel out each other.

3.5 Conclusion

We develop a heterogeneous-firm model incorporating the occupational choice of individuals to become workers or entrepreneurs. This model delivers two messages. First, we shed light on the fiscal origin of the decline in the labor share. More specifically, we show that the corporate-friendly fiscal policy decreases the labor share, which is ex-ante not clear when capital is considered as the counterpart of labor as is common in the literature. By distinguishing entrepreneurial profits and wages by introducing the occupational choice, we reveal that corporate-friendly fiscal policy decreases the labor share.

Second, we highlight that this occupational choice affected by corporate-friendly fiscal policy has a general equilibrium effect that offsets the initial decrease of the labor share through the entry of entrepreneurs and the competition between them. The existence of this general equilibrium effect above and beyond the direct impact though redistribution implies the importance of flexible entry adjustment because the labor share overshoots when the entry adjustment is rigid. When corporate-friendly fiscal policy is implemented under rigid environment, incumbent entrepreneurs enjoy the benefits, and the labor share declines more than it should do. Therefore, enhancing competition between entrepreneurs by removing frictions of the entry adjustment should support stabilizing the labor share.

This study can be extended to several directions. First, by incorporating risk preferences of entrepreneurs, stochastic environment, and frictional entry adjustment to this model, rich dynamic general equilibrium implications of fiscal policy and macroeconomic policy should be obtained. Second, the impact of other sources that affect the occupational choice of individuals such as minimum wage, innovation, international trade could be explored through the lens of this model.

3.A Figures

Figure 3.1: Equilibrium

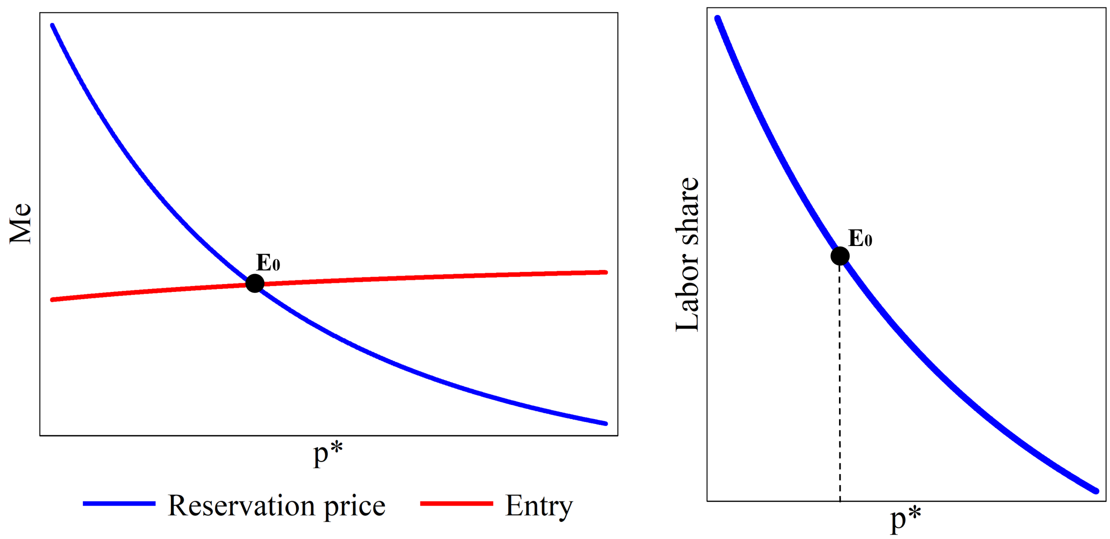


Figure 3.2: Corporate-friendly fiscal policy

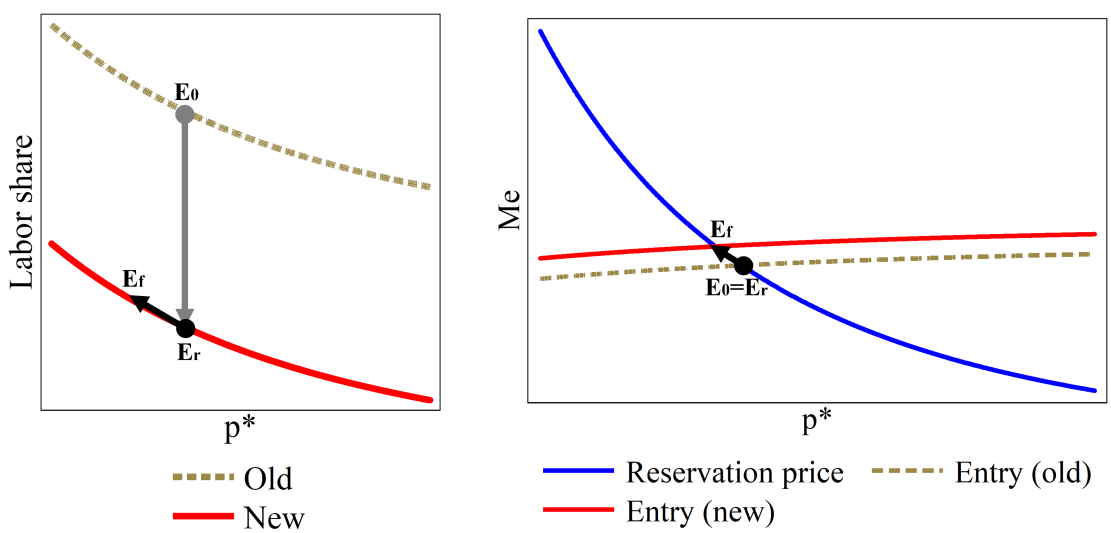


Figure 3.3: Equilibrium under Pareto distribution

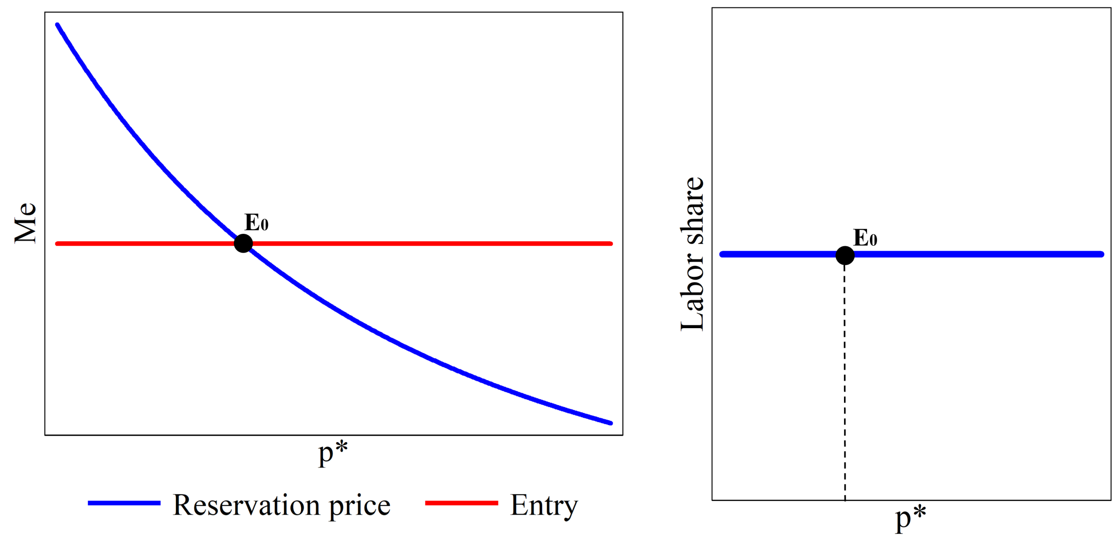
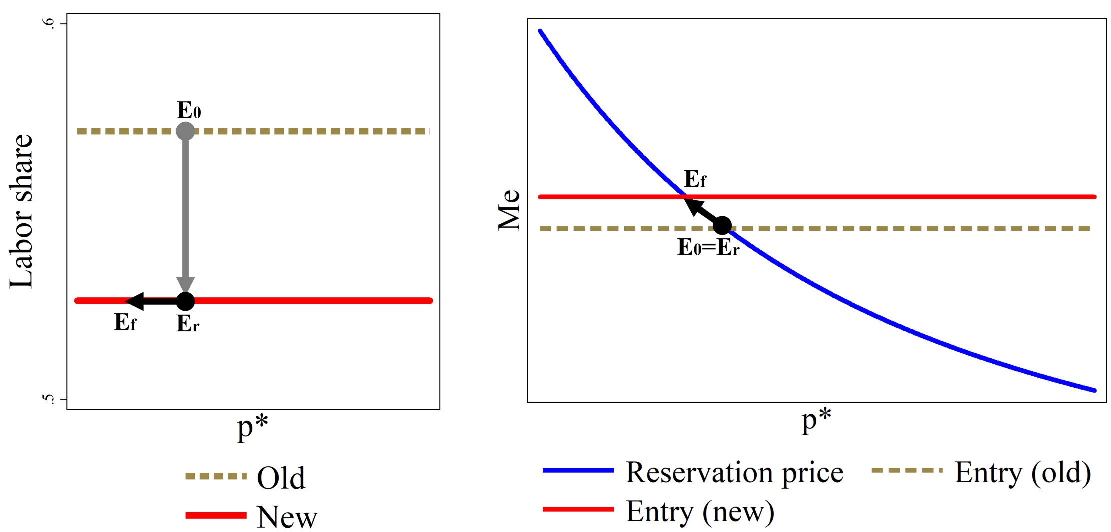


Figure 3.4: Corporate-friendly fiscal policy under Pareto distribution



Appendix A

Appendix to Chapter 1

A.1 Alternative approach to modeling competition: productivity approach

In this section, the productivity improvement of Chinese firms is directly included in the model to examine the impact of competition with China on innovation. The quality intensity parameter δ_s is assumed to be endogenous in the level of utility as in the main text. Suppose the productivity of Chinese firms increase. Recall that the price index (1.4) can be rewritten as

$$P_s = \left(P_{cn,s}^{1-\sigma_s} + \sum_{k \neq cn} P_{ks}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}, \text{ where } P_{cn,s} = \left(M_{cn} \int_{\phi_{cn,s}}^{\infty} z_{cn,s}(\phi)^{\delta_s(\sigma_s - 1)} p_{cn,s}(\phi)^{1-\sigma_s} dG(\phi) \right)^{\frac{1}{1-\sigma_s}}.$$

It can be shown that the quality adjusted prices that comprise $P_{cn,s}$ is

$$z_{cn,s}(\phi)^{\delta_s(\sigma_s-1)} p_{cn,s}^{1-\sigma_s} = \left(\frac{\sigma_s}{\sigma_s - 1}\right)^{1-\sigma_s} \left(\frac{F_s(\alpha - \beta_s)}{\beta_s f_s}\right)^{\frac{\alpha-\beta_s}{\alpha}} \phi^{\xi_s} \phi_s^{\frac{(\alpha-\beta_s)(\sigma_s-1)}{\beta_s}}, \tag{A.1}$$

which is increasing in ϕ. Therefore, the quality adjusted prices of incumbent Chinese firms selling in market s fall as their productivity improves. As a result, the price index in country s falls when Chinese firms' productivity improves. Then, the utility of consumers in country s increases, and Proposition 1, Proposition 2, and Proposition 3 of the main text hold. Furthermore, since this innovation response is not limited to Korean firms, high productivity firms of other countries engage in more innovation as well. Therefore, the second wave of productivity improvement follows the rise of Chinese firms. This general equilibrium effect accelerates the innovation of high-productivity firms further.

A.2 Data Appendix

A.2.1 KIPRIS - KIS-VALUE Matching

The KIPRIS provides an Application Programming Interface (API) service to download bibliographic information of the universe of South Korean patents starting from 1948. Using *requests* command of Python, I download detailed information including application number, assignees' name and address with their unique identifiers, inventors' name and address, technology classification, title, abstract, specific claims, registration status, type of application, registration status, and citation.[1] Regarding citation information, one of the barriers in linking citing patents and cited patents is that the information has been recorded with their publication numbers or registration numbers, not their application numbers. Since publication numbers may not unique to application numbers especially before the 2000s, citation information has not been widely used for South Korean patent data. However, the KIPRIS recently resolved the problem by linking citing and cited patents using application numbers. This study relies on this updated information. In practice I utilize citation chosen by examiners instead of citation information submitted by applicants since the former is considered as more relevant to the quality of patent. Moreover, since old patents are likely to be cited for a longer time, I only count citations of the first five years after application following Bloom and Van Reenen (2002). The downloaded patent information is matched to firm-level dataset KIS-VALUE following these steps.

1. Download firm-level information from the KIS-VALUE including corporation registration number and business registration number.

2. Download a concordance table from the KIPRIS that links patent applicant IDs to corporation registration numbers and business registration numbers.

3. Match patent applicant IDs to corporation registration numbers and business registration numbers in the KIS-VALUE data. Then, two matched datasets are merged. Sometimes, at this step, one patent ID may be assigned to multiple firms. In that case, priority is given to

[1] *http://plus.kipris.or.kr/openapi/rest/CitingService/citingInfo?standardCitationApplicationNumber={}& accessKey={}.format(appnumber, ServiceKey)* is used to request citation information. For other bibliographic information, *http://plus.kipris.or.kr/kipo-api/kipi/patUtiModInfoSearchSevice/getBibliographyDetailInfoSearch? applicationNumber=.{}&ServiceKey={}.format(appnumber, ServiceKey)* is used to request information.

observations matched with corporation registration numbers.

4. Use corporation registration numbers of the KIS-VALUE dataset to web-scrape patent applicant IDs on the Korean Intellectual Property Office website (http://patent.go.kr).

5. Combine matched observations obtained from step 3 and step 4, and drop duplicate observations to finalize the data.

Through these steps, 17,346 firms in the KIS-VALUE dataset are matched with patent applicant IDs. Importantly, each firm may have more than one patent ID since multiple IDs can be assigned to a firm due to name change, duplicate ID applications, or pure mistakes. Therefore, when patent IDs are used as firm-identifiers, patents of the same firm may be mistakenly regarded as those of different firms. By utilizing corporation registration numbers and business registration numbers, this problem can be mitigated in this study. Lee et al. (2020) take a similar approach to match patent data to another firm-level dataset Dataguide 5.0. However, the concordance table provided by the KIPRIS was not available at that time. On top of that, the citation information issue was not still resolved. As a result, I can analyze more firms (compared to 14,083 firms) with better-matched citation information.

A.2.2 KSIC - ISIC Matching

5-digit KSIC 9th revision industry classification is matched to 4-digit ISIC 3rd revision following the concordance table provided by Statistics Korea. Since firms in the KIS-VALUE dataset report their 5-digit KSIC 9 industry, this concordance table is used to construct a firm-level export competition measure. However, some firms report their industry in 3-digit or 4-digit to describe the scope of their products better. In this case, multiple 4-digit ISIC industries may become candidates for the firm's industry. When this happens, 4-digit ISIC industry matched to 5-digit KSIC industry with the largest shipment value in 2007 is selected as the firm's industry. For instance, a firm reports its industry as 31990, which covers 31991 and 31999. 4-digit ISIC matched to 31991 is 3592, whereas 31999 is linked to 3599. In this case, since the shipment of 31991 industry is smaller than 31999 industry (18,338 million KRW v.s. 69,504 million KRW), the firm's industry is converted to 3599 ISIC industry.

A.2.3 Data Correction for Competition Measures

Raw firm-level data and trade data are corrected to construct the measures of export competition and import competition in a consistent manner. First, raw firm-level financial data are corrected since they include observations with the export share greater than one (exports/sales>1). When those observations have domestic sales information and the sum of domestic sales and exports is smaller than reported sales information, I replace the reported sales information with the sum of domestic sales and exports. Even after this correction, the export share is larger than one for 36 observations. These observations are dropped.

Second, raw trade data are corrected to reflect the independence countries between the period of interest. More specifically, those countries are regarded as one country during the sample period, and trade flow related to those countries are aggregated. For instance, since Timore-Leste became independent from Indonesia in 2002, trade with Timore-Leste is added to trade with Indonesia. Similarly, since Serbia Montenegro became Serbia and Montenegro in 2006, these countries are considered as one country in the analysis. South Sudan and Sudan are also regarded as one country in an extended sample analysis since they became separate countries in 2011.

A.3 Prevalence of Export Competition and Import Competition

Table A.1 shows how prevalent export competition with China is by industry. Market in column (1) is defined as possible third markets that Korean firms and Chinese firms can export to in 2001. More specifically, for each country-industry cell with positive imports in 2001 is counted as markets, where country excludes South Korea and China and industry is defined by the 4-digit ISIC. In this regard, the number of markets in column (1) indicates all possible export markets within 2-digit industry that Korean firms may compete with Chinese firms in 2001. Column (2) shows the share of markets that Korean firms actually export to in 2001. Column (3) shows the share of Korean export destinations where the Chinese share of imports increased between 2001 and 2007. Finally, Column (4) indicates the average change in Chinese share of imports in Korean export destinations. For instance, the first row implies that there are 3,691 third markets in food product and Korean firms export to 1,114 (30.18%) of these markets. Among these 1,114 Korean export destinations, Chinese share of imports increased in 787 (70.65%) markets, and the Chinese share of imports increased 1.94%p on average in those 1,114 Korean export destinations. Overall, column (3) shows that export competition intensified in 84.2% of Korean export markets on average, and column (4) shows that Chinese share increased by 7.4%p in Korean export destinations. Table A.2 reports the similar results using Korean import market. Each 4-digit ISIC industry which KIS-VALUE manufacturing firms belong to is defined as market. Column (1) shows that import competition with China strengthened in 92.5% of the markets on average, whereas column (4) shows that Chinese share of imports increased 14.4%p on average. Both export competition and import competition were prevalent and large in magnitude during the sample period.

Figure A.1 and Figure A.2 visualize these results. Two things are noteworthy. First, both export competition and import competition are prevalent among Korean industries. For each 2-digit industry, the Chinese share of imports increased in at least 45% of Korean export markets and in at least 60% of Korean domestic markets. Second, the average increases in the Chinese share in Korean export destinations and in Korean domestic market are heterogeneous across industries. The average increase in the Chinese share of imports is as high as 13.45%p for Korean export markets in apparel industry, whereas it is as low as 0.99%p in petroleum products. Similarly, the average increase in the Chinese share of imports in Korean market is as high as 37.45%p for office, accounting, and computing machinery, whereas it is as low as 2.86%p for petroleum products.

A.4 Additional Estimation Results using R&D Expenditures

It is possible that patent applications may not capture the actual innovation of firms for several reasons. First, firms may keep their innovation as a secret without applying for patents. Second, this patenting decision could be affected by competition with China, which results in the change in the number of patent applications even if there is no change in innovation per se. To mitigate this concern, research and development (R&D) expenditures can be used to capture the innovation efforts.

South Korean accounting standards require firms to distinguish expenditures on research from those on development. R&D expenditures those do not meet specific requirements such as the technical feasibility are reported as research expense, whereas those meeting the requirements are reported as investments in intangible asset, which are then amortized. Therefore, the R&D

expenditures of firms in the KIS-VALUE dataset are measured as follows:

$$R\&D = Ordinary\ R\&D\ expenses + Current\ period\ R\&D\ expenses - Prior\ period\ R\&D\ expenses \\ + Amortization\ of\ R\&D\ expenses + Current\ period\ capitalized\ R\&D\ expenses. \quad \text{(A.2)}$$

However, since not all items are always available for all firms, the results in this section should be interpreted with caution.

To examine the overall impact of competition with China on the R&D expenditures of South Korean firms, the following equation is estimated:

$$\ln(R\&D_{f,t}) = \alpha\Delta IC_{f,t-1} + \beta\Delta XC_{f,t-1} + \gamma ln(R\&D_{f,0}) + \delta\Delta Xsize_{f,t-1} + X'_{f,t}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}, \quad \text{(A.3)}$$

where the pre-sample period average R&D expenditures $ln(R\&D_{f,0})$ is included as a control similar to the main regression. Turning to the heterogeneous impact of competition with China, the following equation is estimated:

$$\ln(R\&D_{f,t}) = \alpha_1\Delta IC_{f,t-1} + \alpha_2\Delta IC_{f,t-1} \times Decile_f + \beta_1\Delta XC_{f,t-1} + \beta_2\Delta XC_{f,t-1} \times Decile_f + \\ \zeta Decile_f + \gamma ln(R\&D_{f,0}) + \delta\Delta Xsize_{f,t-1} + X'_{f,t}\Lambda + \mu_t + \mu_i + \varepsilon_{f,t}. \quad \text{(A.4)}$$

Table A.3 shows the overall impact of competition with China on the R&D expenditures of firms. Consistent with the main findings using the number of patent applications as a dependent variable, the overall impact of export competition on R&D expenditures is positive and significant for all specifications, whereas that of import competition is indistinguishable from zero. Table A.4 shows the heterogeneous responses between firms. Similar to the main analysis, only high-productivity firms increase innovation facing tougher export competition with China. All coefficients related to the interaction of export competition and productivity decile are positive and significant as expected for all models. A coefficient for the interaction with import competition and productivity decile in column (5) is negative and significant unlike the main analysis. However, this result is sensitive to specifications in that sign of this coefficient changes by specifications and no significant results are found. Moreover, since using R&D expenditures reduces the number of observations, these results may suffer from the weak instrument problem as is suggested by the first stage F-statistics

A.5 Additional Estimation Results from Alternative Specifications

The main results rely on the first-differenced specification following Aghion et al. (2022). In order to show that these results are not specific to the estimation strategy adopted in the main analysis, the results using two alternative specifications are reported. First, the number of patent applications is interpreted as the level of innovation instead of interpreting the number of patent as the increase in patent stock. Then, the level of innovation is regressed on the level of competition measures and other variables following Aghion et al. (2018). More formally, the following equation is estimated:

$$INN_{f,t} = \alpha IC_{f,t} + \beta XC_{f,t} + X'_{f,t}\Lambda + \mu Xsize_{f,t} + \delta_f + \delta_{i,t} + \varepsilon_{f,t}, \tag{A.5}$$

where $INN_{f,t}$ is the number of patent applications ($\Delta P_{f,t}$) in the main analysis. Firm-level controls $X'_{f,t}$ include sales, employment, and tangible asset of firms (all in logarithms), and the export market size $Xsize_{f,t}$ that each firm effectively faces. Time-invariant unobservable firm characteristics are captured by the firm fixed effect δ_f, and industry-specific shocks are captured by the 2-digit industry-time fixed effect $\delta_{i,t}$. Standard errors are clustered by 4-digit industry. To examine the heterogeneous impact, the interaction terms with initial productivity decile are included as follows:

$$INN_{f,t} = \alpha_1 IC_{f,t} + \alpha_2 IC_{f,t} \times Decile_f + \beta_1 XC_{f,t} + \beta_2 XC_{f,t} \times Decile_f + X'_{f,t}\Lambda + \mu Xsize_{f,t} + \delta_f + \delta_{i,t} + \varepsilon_{f,t}. \tag{A.6}$$

Table A.5 and A.6 show that comparable results are obtained. Column (5), the most preferred specification, shows that the overall impact of export competition is positive and significant at the 5 percent level. In addition, strong and significant heterogeneous responses are found for export competition.

Second, similar to Bloom et al. (2016) and Autor et al. (2020a), the growth in the number of patent applications is used as the dependent variable to examine the impact of competition shocks on innovation. More specifically, the following equation is estimated:

$$\Delta INN_{f,t} = \alpha \Delta IC_{f,t-1} + \beta \Delta XC_{f,t-1} + X'_{f,t}\Lambda + \gamma ln(1+INN_{f,0}) + \mu \Delta Xsize_{f,t-1} + \delta_i + \delta_t + \varepsilon_{f,t}, \tag{A.7}$$

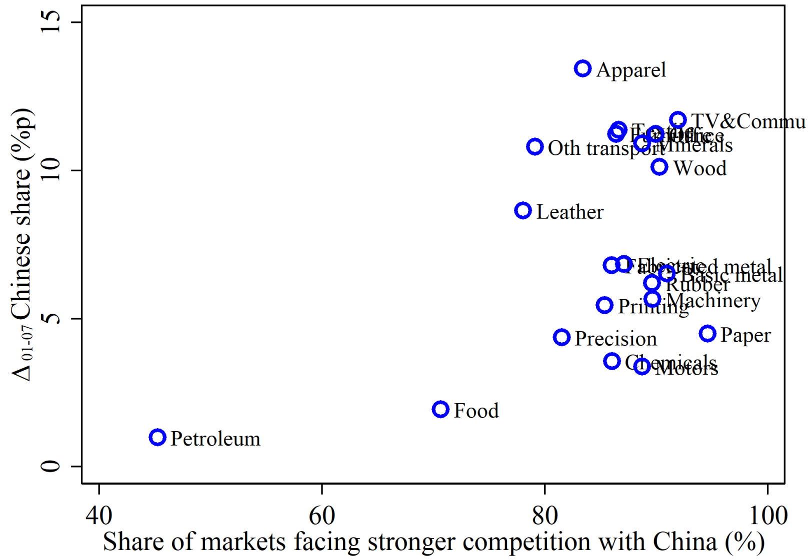
where Δ indicates the Davis-Haltiwanger growth rate for all variables. Time varying control variables include sales, employment, and tangible asset of firms (all in logarithms). Pre-sample period innovation, 2-digit industry fixed effects, and time fixed effects are included to capture unobservable characteristics and macroeconomic shocks. In addition, to examine the heterogeneous responses, the interaction terms with initial productivity decile are included:

$$\begin{aligned} \Delta INN_{f,t} = {} & \alpha_1 \Delta IC_{f,t-1} + \alpha_2 \Delta IC_{f,t-1} \times Decile_f + \beta_1 \Delta XC_{f,t-1} + \beta_2 \Delta XC_{f,t-1} \times Decile_f + \\ & \eta Decile_f + X'_{f,t}\Lambda + \gamma ln(1+INN_{f,0}) + \mu \Delta Xsize_{f,t-1} + \delta_i + \delta_t + \varepsilon_{f,t}. \end{aligned} \tag{A.8}$$

Table A.7 and A.8 show that the results are qualitatively similar, in particular for the heterogeneous responses. Column (5) of Table A.8 shows that firms with the lowest initial productivity decile decrease innovation facing either import competition shock or export competition shock, and the response is increasing in productivity decile. The heterogeneity is more precisely estimated for the export competition.

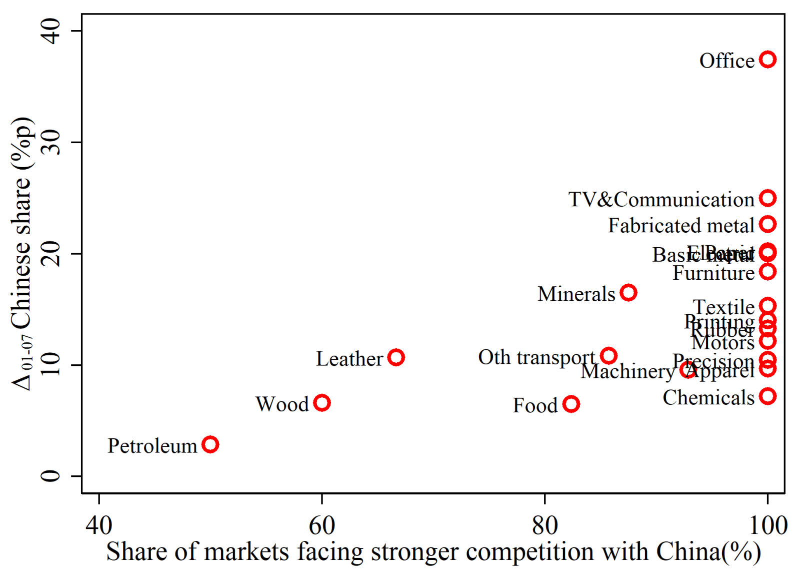
A.6 Figures

Figure A.1: Prevalence of export competition with China in third countries



Notes: Each country-product cell with positive Korean manufacturing exports in 2001 is defined as a market. Each circle represents the share of markets that experienced an increase in export competition and the change in the average Chinese share of imports in those markets by 2-digit industry.

Figure A.2: Prevalence of import competition with China in South Korea



Notes: Each 4-digit product cell which KIS-VALUE manufacturing firms belong to is defined as a market. Each circle represents the share of markets that experienced an increase in import competition and the change in the average Chinese share of imports in those markets by 2-digit industry.

A.7 Tables

Table A.1: Prevalence of export competition with China in third countries

ISIC	Description	# of markets (Cnty×Ind) (1)	Korean export destination (%) (2)	Chinese share increase (%) (3)	Δ Chinese share (%p) (4)
15	Food products and beverages	3691	30.18	70.65	1.94
17	Textiles	1307	65.03	86.59	11.38
18	Apparel	419	53.22	83.41	13.45
19	Leather products and footwear	639	54.15	78.03	8.65
20	Wood products, straw, and plaiting materials	1081	27.57	90.27	10.13
21	Paper and paper products	653	59.42	94.59	4.49
22	Publishing, printing and reproduction of recorded media	1284	48.91	85.35	5.46
23	Coke and refined petroleum products	586	23.38	45.26	0.99
24	Chemicals and chemical products	1952	58.97	86.01	3.56
25	Rubber and plastics products	654	80.89	89.60	6.21
26	Other non-metallic mineral products	1736	36.23	88.71	10.92
27	Basic metals	436	65.83	90.94	6.52
28	Fabricated metal product	1081	54.76	85.98	6.81
29	Machinery and equipment	3238	57.26	89.64	5.67
30	Office, accounting and computing machinery	218	77.52	89.94	11.24
31	Electrical machinery and apparatus	1308	68.04	87.08	6.84
32	Radio, television and communication equipment and apparatus	654	70.03	91.92	11.71
33	Medical, precision and optical instruments, watches and clocks	1087	62.65	81.50	4.37
34	Motor vehicles, trailers and semi-trailers	654	73.09	88.70	3.38
35	Other transport equipment	1495	33.91	79.09	10.80
36	Furniture	1304	58.05	86.39	11.24

Notes: This table shows the number of third-country markets (country and 4-digit industry pair with positive imports in 2001), the share of markets South Korea exports to, and the share of Korean export destination markets where Chinese share of imports increases between 2001 and 2007, and the average magnitude of the increase in each 2-digit ISIC industry.

Table A.2: Prevalence of import competition with China in the domestic market

ISIC	Description	Chinese share increase (%) (1)	Δ Chinese share (%p) (2)
15	Food products and beverages	82.35	6.51
17	Textiles	100.00	15.30
18	Apparel	100.00	9.67
19	Leather products and footwear	66.67	10.69
20	Wood products, straw, and plaiting materials	60.00	6.62
21	Paper and paper products	100.00	20.21
22	Publishing, printing and reproduction of recorded media	100.00	14.02
23	Coke and refined petroleum products	50.00	2.86
24	Chemicals and chemical products	100.00	7.21
25	Rubber and plastics products	100.00	13.29
26	Other non-metallic mineral products	87.50	16.51
27	Basic metals	100.00	20.04
28	Fabricated metal product	100.00	22.66
29	Machinery and equipment	92.86	9.59
30	Office, accounting and computing machinery	100.00	37.45
31	Electrical machinery and apparatus	100.00	20.18
32	Radio, television and communication equipment and apparatus	100.00	25.01
33	Medical, precision and optical instruments, watches and clocks	100.00	10.45
34	Motor vehicles, trailers and semi-trailers	100.00	12.17
35	Other transport equipment	85.71	10.84
36	Furniture	100.00	18.41

Notes: This table shows the share of South Korean markets (4-digit ISIC industry which KIS-VALUE manufacturing firms belong to) where Chinese share of imports increases between 2001 and 2007, and the average magnitude of the increase in each 2-digit ISIC industry.

Table A.3: Overall impact of competition with China on R&D expenditures

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	0.006	-0.344		-0.013	-0.734
	(0.047)	(0.477)		(0.047)	(0.597)
$\Delta XC_{f,t-1}$			0.532**	0.537**	0.803**
			(0.225)	(0.227)	(0.318)
1st stage F-statistics		23.264			17.483
N	8,093	8,093	8,093	8,093	8,093

Notes: R&D expenditures are used as a dependent variable. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of R&D expenditures, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A.4: Heterogeneous impact of competition with China on R&D expenditures

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.074	0.671		-0.050	0.892
	(0.110)	(0.673)		(0.111)	(0.716)
$\Delta IC_{f,t-1} \times Decile_f$	0.014	-0.215		0.007	-0.371**
	(0.019)	(0.133)		(0.019)	(0.178)
$\Delta XC_{f,t-1}$			-0.617	-0.598	-0.712
			(0.742)	(0.748)	(0.834)
$\Delta XC_{f,t-1} \times Decile_f$			0.187*	0.184*	0.286**
			(0.110)	(0.111)	(0.127)
Cutoff decile for IC	7	-	-	9	-
Cutoff decile for XC	-	-	5	5	4
1st stage F-statistics		6.178			3.883
N	8,093	8,093	8,093	8,093	8,093

Notes: R&D expenditures are used as a dependent variable. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include the lagged growth of export market size, year fixed effects, 2-digit industry fixed effects, the pre-sample period (1995-2000) average of R&D expenditures, sales, employment, and tangible assets (all in logarithms). Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A.5: Overall impact of competition with China on innovation (level-level)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$IC_{f,t}$	-0.478*	-0.162		-0.303	0.146
	(0.255)	(0.349)		(0.233)	(0.255)
$XC_{f,t}$			16.418**	16.237**	16.506**
			(6.512)	(6.504)	(6.398)
1st stage F-statistics		24.238			23.670
N	21,543	21,543	21,543	21,543	21,543

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include firm fixed effects, 2-digit industry-year fixed effects, time-varying firm-level sales, employment, tangible assets (all in logarithms), and export market size. Standard errors in parentheses are clustered at the 4-digit industry level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A.6: Heterogeneous impact of competition with China on innovation (level-level)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$IC_{f,t}$	-0.899*	-0.670		-0.445	0.099
	(0.503)	(0.550)		(0.393)	(0.332)
$IC_{f,t} \times Decile_f$	0.092	0.112*		0.031	0.032
	(0.062)	(0.061)		(0.044)	(0.029)
$XC_{f,t}$			-21.420***	-21.497***	-21.168***
			(4.363)	(4.304)	(4.311)
$XC_{f,t} \times Decile_f$			5.974***	5.950***	5.950***
			(1.549)	(1.535)	(1.540)
Cutoff decile for IC	-	8	-	-	1
Cutoff decile for XC	-	-	5	5	5
1st stage F-statistics		12.048			11.725
N	21,543	21,543	21,543	21,543	21,543

Notes: The number of patent applications is used as the measure of innovation. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include firm fixed effects, 2-digit industry-year fixed effects, time-varying firm-level sales, employment, tangible assets (all in logarithms), and export market size. Standard errors in parentheses are clustered at the 4-digit industry level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A.7: Overall impact of competition with China on innovation (growth of innovation)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.063**	-0.266		-0.063**	-0.281
	(0.030)	(0.182)		(0.030)	(0.196)
$\Delta XC_{f,t-1}$			-0.038	-0.014	0.069
			(0.107)	(0.107)	(0.129)
1st stage F-statistics		120.779			109.773
N	21,327	21,327	21,327	21,327	21,327

Notes: The growth rate of patent applications is used as a dependent variable. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. All models include year fixed effects, 2-digit industry fixed effects, pre-sample period (1995-2000) average innovation, time-varying firm-level sales, employment, tangible assets (all in logarithms), and the lagged export market size growth. Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Table A.8: Heterogeneous impact of competition with China on innovation (growth of innovation)

	OLS (1)	2SLS (2)	OLS (3)	OLS (4)	2SLS (5)
$\Delta IC_{f,t-1}$	-0.079	-0.533**		-0.070	-0.495**
	(0.051)	(0.233)		(0.051)	(0.239)
$\Delta IC_{f,t-1} \times Decile_f$	0.004	0.067		0.002	0.056
	(0.009)	(0.041)		(0.009)	(0.044)
$\Delta XC_{f,t-1}$			-0.650***	-0.617***	-0.451**
			(0.177)	(0.178)	(0.204)
$\Delta XC_{f,t-1} \times Decile_f$			0.104***	0.102***	0.079***
			(0.026)	(0.027)	(0.030)
Cutoff decile for IC	-	9	-	-	10
Cutoff decile for XC	-	-	8	8	7
1st stage F-statistics		38.622			29.035
N	21,327	21,327	21,327	21,327	21,327

Notes: The growth rate of patent applications is used as a dependent variable. Columns (1), (3), and (4) report the OLS results, whereas columns (2) and (5) report the 2SLS results. Cutoff decile corresponds to the first decile that overall effect becomes positive. All models include year fixed effects, 2-digit industry fixed effects, pre-sample period (1995-2000) average innovation, time-varying firm-level sales, employment, tangible assets (all in logarithms), and the lagged export market size growth. Standard errors in parentheses are clustered at the firm level. The first stage F statistics refers to Kleibergen-Paap F-statistics. Sample includes manufacturing firms with at least one patent application between 2001 and 2007. ***, **, and * indicate 0.01, 0.05, and 0.1 significance level, respectively.

Appendix B

Appendix to Chapter 3

B.1 Reservation Price and Demand Function Derivation

We can derive the reservation price p^* using the fact that $D_i(p^*) = 0$ and derive $D_i(p_\omega)$ using the p^*. First, we can rewrite (3.1) with the prices of $\omega \notin \Omega$ as p^* as

$$e\left(\mathbf{p}\right) = \left[\alpha \int_\Omega p_\omega^2 d\omega + \alpha(\tilde{N} - N)p^{*2} + \beta \left(\int_\Omega p_\omega d\omega\right)^2 + 2\beta(\tilde{N} - N)p^* \int_\Omega p_\omega d\omega + \beta(\tilde{N} - N)^2 p^{*2}\right]^{1/2}. \tag{B.1}$$

Applying Shephard's lemma, we differentiate (B.1) with respect to p^*, divide it by $\tilde{N} - N$, and multiply it by utility u to derive the demand for a good with price p^*. This yields

$$D_i(p^*) = e(\mathbf{p})^{-1}\left[\alpha p^* + \beta \int_\Omega p_\omega d\omega + \beta p^*(\tilde{N} - N)\right]u \tag{B.2}$$

Setting this demand equal to zero, we simplify the reservation price as

$$p^* = \frac{\int_\Omega p_\omega d\omega}{N - \tilde{N} - \alpha/\beta}, \tag{B.3}$$

Now, to derive the demand function of a good with price p_ω, we differentiate (B.1) with respect to p_ω and multiply it by utility $u = \tau_i(y_i)e(\mathbf{p})^{-1}$.

$$D_i(p_\omega) = \frac{1}{2}e(\mathbf{p})^{-1}\left[2\alpha p_\omega + 2\beta \int_\Omega p_\omega d\omega + 2\beta(\tilde{N} - N)p^*\right] \times \tau_i(y_i)e(\mathbf{p})^{-1} \tag{B.4}$$

$$= \alpha(p_\omega - p^*)e(\mathbf{p})^{-2}\tau_i(y_i), \tag{B.5}$$

where the second equality holds since we use (3.2) to simplify the terms in the bracket.

B.2 Expenditure Function Derivation

Note that (B.1) can be rewritten as

$$e\left(\mathbf{p}\right)=\left[\alpha\int_{\Omega}p_{\omega}^{2}d\omega+\beta\left(\int_{\Omega}p_{\omega}d\omega\right)^{2}+p^{*}(\tilde{N}-N)\big(\alpha p^{*}+2\beta\int_{\Omega}p_{\omega}d\omega+\beta(\tilde{N}-N)p^{*}\big)\right]^{1/2}. \quad \text{(B.6)}$$

Then, by replacing p^* using (3.2), it becomes

$$e\left(\mathbf{p}\right)=\left[\alpha\int_{\Omega}p_{\omega}^{2}d\omega-\frac{\alpha}{N-\tilde{N}-\alpha/\beta}\big(\int_{\Omega}p_{\omega}d\omega\big)^{2}\right]^{1/2}. \quad \text{(B.7)}$$

This simplifies further as

$$\begin{aligned}
e\left(\mathbf{p}\right) &= \left[\alpha\int_{\Omega}p_{\omega}^{2}d\omega-\alpha p^{*}\big(\int_{\Omega}p_{\omega}d\omega\big)\right]^{1/2} && \text{(B.8)}\\
&= \left[\alpha\int_{\Omega}p_{\omega}(p_{\omega}-p^{*})d\omega\right]^{1/2} && \text{(B.9)}\\
&= \left[-\frac{\alpha}{4}M_{e}\int_{c<p^{*}}(p^{*2}-c^{2})dF(c)\right]^{1/2} && \text{(B.10)}
\end{aligned}$$

where the first equality uses (3.2), and the third equality rewrites the previous equation by replacing p_ω with the optimal price $\frac{p^*+c}{2}$. We also use the fact that $\int_\Omega d\omega = M_e\int_{c<p^*}dF(c)$ Finally, by squaring both sides, we have

$$e\left(\mathbf{p}\right)^{2}=-\frac{\alpha}{4}M_{e}\int_{c<p^{*}}(p^{*2}-c^{2})dF(c)$$

B.3 Entry Equation Derivation

Note that the fiscal balance condition (3.9) can be rewritten as

$$M_{e}\int\tau_{e}\left(\pi\left(c\right)\right)dF\left(c\right)=M_{w}\left(1-\tau_{w}\left(1\right)\right)+M_{e}\int\pi\left(c\right)dF\left(c\right)-G. \quad \text{(B.11)}$$

Note further that by multiplying M_e, the free entry condition (3.12) can be rewritten as

$$M_e \tau_w(1) = M_e \int \tau_e\left(\pi\left(c\right)\right) dF\left(c\right). \tag{B.12}$$

Then, using (B.11), (B.12) becomes

$$M_e \tau_w(1) = M_w\left(1 - \tau_w\left(1\right)\right) + M_e \int \pi\left(c\right) dF\left(c\right) - G. \tag{B.13}$$

Using $(M_e + M_w)\tau_w(1) = \tau_w(1)$ and $\int \pi\left(c\right) dF\left(c\right) = \int_{c<p^*} \pi\left(c\right) dF\left(c\right)$ since $\pi(c) = 0$ for $c \geq \bar{c}$, this equation becomes

$$M_w = \tau_w\left(1\right) - M_e \int_{c<p^*} \pi\left(c\right) dF\left(c\right) + G. \tag{B.14}$$

Then, by replacing $\pi(c)$ with (3.7), and substituting $e(\mathbf{p})^2$ with (3.8), this becomes

$$M_w = \tau_w\left(1\right) - \frac{\int_{c<p^*}(p^* - c)^2 dF(c)}{\int_{c<p^*}(p^{*2} - c^2)dF(c)} Y + G. \tag{B.15}$$

Now, using $G = gY$ and $Y = \frac{\int_{c<p^*}(p^{*2}-c^2)dF(c)}{2\int_{c<p^*}(p^*c-c^2)dF(c)} M_w$ from the labor market equilibrium condition (3.11), this becomes

$$M_w = \tau_w\left(1\right) - \frac{\int_{c<p^*}\left(p^* - c\right)^2 dF\left(c\right)}{2\int_{c<p^*}\left(p^*c - c^2\right) dF\left(c\right)} M_w + g\frac{\int_{c<p^*}\left(p^{*2} - c^2\right)dF(c)}{2\int_{c<p^*}\left(p^*c - c^2\right) dF\left(c\right)} M_w. \tag{B.16}$$

Finally, by rearranging, and replacing M_w with $1 - M_e$, we get

$$M_e = 1 - \frac{2\tau_w\left(1\right)}{1-g} \times \frac{\int_{c<p^*}\left(p^*c - c^2\right) dF\left(c\right)}{\int_{c<p^*}\left(p^{*2} - c^2\right)dF(c)} \tag{B.17}$$

$$= 1 - \frac{\tau_w\left(1\right)}{1-g} \times A(p^*) \tag{B.18}$$

B.4 Slope of Reservation Price Curve and Entry Curve

The entry curve is upward-sloping when bounded Pareto distribution is assumed. However, it is a horizontal line when unbounded Pareto distribution is assumed as shown in the main text. Distributional assumption matters for the slope of the entry curve. However, the reservation price curve is always downward-sloping regardless of distributional assumption.

(1) Reservation price equation

By differentiating the reservation price equation (3.16), we get

$$\frac{dM_e}{dp^*} = \frac{\tilde{N} + \frac{\alpha}{\beta}}{\int_{c<p^*} \frac{p^*-c}{2} dF(c)} - \frac{p^* \left(\tilde{N} + \frac{\alpha}{\beta}\right) \frac{F(p^*)}{2}}{\left(\int_{c<p^*} \frac{p^*-c}{2} dF(c)\right)^2}, \tag{B.19}$$

Since the common factor $\frac{\tilde{N}+\frac{\alpha}{\beta}}{\left(\int_{c<p^*} \frac{p^*-c}{2} dF(c)\right)^2} > 0$, the sign of $\frac{dM_e}{dp^*}$ is determined by

$$\begin{aligned} sign[\frac{dM_e}{dp^*}] &= sign\big[\int_{c<p^*} \frac{p^*-c}{2} dF(c) - \frac{p^* F(p^*)}{2}] \\ &= sign\big[-\int_{c<p^*} \frac{c}{2} dF(c)\big] \end{aligned}$$

Therefore, without any distributional assumptions, we get $\frac{dM_e}{dp^*} < 0$. The reservation price curve is downward-sloping.

(2) Entry equation

When the bounded Pareto distribution is assumed, the entry equation is

$$M_e = 1 - \frac{\tau_w\,(1)}{1-g} \times A(p^*)$$

where

$$A(p^*) = \frac{2\theta}{\theta+1} \times \frac{p^{*\theta+2} - (\theta+2)p^* b^{\theta+1} + (\theta+1)b^{\theta+2}}{2p^{*\theta+2} - (\theta+2)p^{*2}b^{\theta} + \theta b^{\theta+2}},$$

and $b > 0$. Therefore,

$$\begin{aligned} sign\big[\frac{dM_e}{dp^*}\big] &= -sign\big[A'(p^*)\big] \\ &= -sign\big[(p^{*\theta+1} - b^{\theta+1})(2p^{*\theta+2} - (\theta+2)p^{*2}b^{\theta} + \theta b^{\theta+2}) - 2(p^{*\theta+2} - (\theta+2)p^* b^{\theta+1} + (\theta+1)b^{\theta+2})(p^{*\theta+1} - p^* b^{\theta})\big] \end{aligned}$$

By defining $x \equiv p^* b^{-1}$ and factoring $b^{2\theta+3}$ out, we have

$$sign\big[\frac{dM_e}{dp^*}\big] = -sign\big[\underbrace{-\theta x^{\theta+3} + 2(\theta+1)x^{\theta+2} - (\theta+2)x^{\theta+1}}_{<0}\underbrace{-(\theta+2)x^2 + 2(\theta+1)x - \theta}_{<0}\big]$$

where the sum of first three terms on the right-hand side is negative since $x > 1$ and the sum of last three terms on the right-hand side is negative since $x > 1$. Therefore, the entry curve is upward sloping.

B.5 Expenditure function differentiation

Since $e(\mathbf{p}) > 0$, the sign of $\frac{\partial e(\mathbf{p})}{\partial p^*}$ is the same as $\frac{\partial e(\mathbf{p})^2}{\partial p^*}$. Note from equation (**??**) that the common factor $-\frac{\alpha(\theta+1)(\tilde{N}+\alpha/\beta)}{2(\theta+2)}p^*$ is increasing in p^* and positive. This implies that the sign of $\frac{\partial e(\mathbf{p})}{\partial p^*}$ is positive when the sign of $\partial \frac{2{p^*}^{\theta+2} - (\theta+2){p^*}^2 b^\theta + \theta b^{\theta+2}}{{p^*}^{\theta+1} - (\theta+1)p^* b^\theta + \theta b^{\theta+1}} / \partial p^*$ is also positive. Note that

$$\begin{aligned} &sign\big[\partial \frac{2{p^*}^{\theta+2} - (\theta+2)\,{p^*}^2 b^\theta + \theta b^{\theta+2}}{{p^*}^{\theta+1} - (\theta+1)\,p^* b^\theta + \theta b^{\theta+1}} / \partial p^*\big] = \\ &\quad sign\big[2(\theta+2)\big({p^*}^{\theta+2} - (\theta+1){p^*}^2 b^\theta + p^* b^{\theta+1}\big) - (\theta+1)\big(2{p^*}^{\theta+2} - (\theta+2){p^*}^2 b^\theta + \theta b^{\theta+2}\big)\big] \end{aligned} \tag{B.20}$$

By defining $x \equiv p^* b^{-1}$ and factoring out positive $b^{\theta+2}$, we have

$$sign\big[\partial \frac{2{p^*}^{\theta+2} - (\theta+2)\,{p^*}^2 b^\theta + \theta b^{\theta+2}}{{p^*}^{\theta+1} - (\theta+1)\,p^* b^\theta + \theta b^{\theta+1}} / \partial p^*\big] = sign\big[2x^{\theta+2} - (\theta+1)(\theta+2)x^2 + 2\theta(\theta+2)x - \theta(\theta+1)\big]. \tag{B.21}$$

Note that equation (B.21) is zero when $x = 1$ and increasing in x when $x \geq 1$.[1] As a result, the sign of $\partial \frac{2{p^*}^{\theta+2} - (\theta+2){p^*}^2 b^\theta + \theta b^{\theta+2}}{{p^*}^{\theta+1} - (\theta+1)p^* b^\theta + \theta b^{\theta+1}} / \partial p^*$ is positive when $p^* \geq b$. Since b is the lower bound of c and p^* is the cutoff marginal cost, this is always true. Therefore, $\frac{\partial e(\mathbf{p})}{\partial p^*}$ is positive.

[1] Differentiating the terms in (B.21) with respect to x, we have $x^{\theta+1} - (\theta+1)x + \theta$, which is zero when $x = 1$ and increasing in $x \geq 1$.

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