Essays in International Economics and Economic Growth

by

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To my fiancée and parents.

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ABSTRACT

This dissertation studies the relationship between openness to trade and economic growth.

The first chapter, co-authored with Younghun Shim, studies how the adoption of foreign technology and local spillovers from such adoption contributed to late industrialization in a developing country during the postwar period. Using novel historical firm-level data for South Korea, we provide causal evidence of direct productivity gains to adopters and local productivity spillovers of the adoption. Based on these empirical findings, we develop a dynamic spatial model with firms' technology adoption decisions and local spillovers. The spillovers induce dynamic complementarity in firms' technology adoption decisions. Because of this dynamic complementarity, the model potentially features multiple steady states. Temporary adoption subsidies can have permanent effects by moving an economy to a new transition path that converges to a higher-productivity steady state. We calibrate our model to the microdata and econometric estimates. We evaluate the effects of the South Korean government policy that temporarily provided adoption subsidies to heavy manufacturing firms in the 1970s. Had no adoption subsidies been provided, South Korea would have converged to a less industrialized steady state in which the heavy manufacturing sectors share of GDP would have been 15 percentage points lower and aggregate welfare would have been 10% lower compared to the steady state with successful industrialization. Thus, temporary subsidies for technology adoption had permanent

effects.

The second chapter, co-authored with Andrei Levchenko, provides causal evidence on the impact of industrial policy on firms' long-term performance and quantifies industrial policy's long-term welfare effects. Using a natural experiment and unique historical data during the Heavy and Chemical Industry (HCI) Drive in South Korea, we find large and persistent effects of firm-level subsidies on firm size. Subsidized firms are larger than those never subsidized even 30 years after subsidies ended. Motivated by this empirical finding, we build a quantitative heterogeneous firm model that rationalizes these persistent effects through a combination of learning-by-doing (LBD) and financial frictions that hinder firms from internalizing LBD. The model is calibrated to firm-level micro data, and its key parameters are disciplined with the econometric estimates. Counterfactual analysis implies that the industrial policy generated larger benefits than costs. If the industrial policy had not been implemented, South Korea's welfare would have been 21-35% lower, depending on how long-lived are the productivity benefits of LBD. Between 80 and 90% of the total welfare difference comes from the long-term effects of the policy.

The third chapter studies the impact of lobbying on resource misallocation and aggregate TFP. I develop a model of heterogeneous firms that can lobby to decrease their output tax/distortion. This lobbying effort can either magnify or mitigate a pre-lobbying level of misallocation depending on whether the more productive firms are initially more distorted. If the more productive firms are burdened by higher pre-lobbying exogenous distortions, they can lobby to overcome these distortions, which increases aggregate total factor productivity (TFP). The TFP influences of lobbying can be affected by international trade as exporters increase their lobbying expenditures due to complementarities between market size and gains from a lower tax post-lobbying. I estimate the model by reduced-form instrumental variables techniques and structurally using firm-level data. I find that lobbying can increase US TFP by 4-7% compared to a counterfactual economy with the same pattern of pre-lobbying distortions, but where lobbying is not allowed.

CHAPTER I

Technology Adoption and Late Industrialization

1.1 Introduction

Large differences in cross-country total factor productivity (TFP) suggest that technology is fundamental to economic development.[1] Based on this observation, many economists and policy-makers have argued that the adoption of advanced technology that rich countries use can make poor countries richer (Parente and Prescott, 2002). Technology adoption can be an even more powerful driving force for economic development if and when technology is at least partially non-rival, and knowledge gained from adopting foreign technology can be spread to other local firms.[2]

In the postwar period, patterns of industrialization among developing countries diverged. The economic base of some developing countries such as South Korea, Taiwan, and Turkey transformed from agriculture to manufacturing, while the economies of many other developing countries remained stagnant. The countries whose base changed to manufacturing achieved industrialization by adopting foreign technology rather than developing their own technology.[3] Their adoption-driven industrializa-

[1] See Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999).

[2] See Romer (1990). Recent studies provide empirical evidence about the existence of knowledge spillovers and find that knowledge spillovers tend to be highly localized (e.g., Jaffe et al., 1993; Kerr and Kominers, 2015; Kantor and Whalley, 2019; Moretti, 2021).

[3] "If industrialization first occurred in England on the basis of invention, and if it occurred in Germany and the United States on the basis of innovation, then it occurs now among "backward" countries on the basis of learning" (Amsden, 1989, p. 4). "Once South Korea reduced its barriers, thereby greatly increasing its TFP, it experienced a development miracle as it used more of the stock of available knowledge" (Parente and Prescott, 2002, p. 4).

tion is known as late industrialization, which differs from the earlier industrialization driven by invention or innovation in the Western countries (Amsden, 1989).[4] A look at what drove the rapid industrialization of these latecomers provides suggestive evidence about the potential importance of technology adoption for economic development. However, little is empirically and quantitatively known about the role of adoption due to the unavailability of detailed data about firms' adoption activities in countries that experienced late industrialization. The key challenge is that technology adoption is typically not observed directly but must be inferred from other equilibrium outcomes.

This paper answers the following question: How do the adoption of foreign technology and its local spillovers contribute to late industrialization? We study South Korea's transition toward heavy manufacturing sectors in the 1970s. South Korea is known for having the most successful and rapid industrialization among the latecomers.[5]

This paper makes three contributions. First, we overcome the empirical challenge in the literature by constructing a novel historical dataset that covers the universe of technology adoption contracts between South Korean and foreign firms. Most of the adopted technology during this period was related to knowledge about how to build and operate plants and capital equipment related to mass production. Using this dataset, we can measure firm-level technology adoption directly at the micro level.

Second, using this novel dataset, we provide reduced-form empirical evidence on the firm-level effects of technology adoption. We develop causal estimates of direct

[4] Building on Gerschenkron's (1952) insights on economic backwardness, Amsden (1989) defines late industrialization as the third wave of industrialization that occurred in a subset of developing countries in the twentieth century based on the adoption of foreign technology.

[5] See Lucas (1993).

productivity gains using a winners vs. losers research design following Greenstone et al. (2010). An empirical challenge related to identifying the direct productivity gains is the fact that firms make adoption decisions endogenously, which leads to the standard selection problem. We deal with this problem by comparing firms that successfully adopted technology and firms that received the approval from the government to pursue foreign technology and made a contract with a foreign firm but failed to adopt technology because the foreign firm canceled the contract due to circumstances unrelated to the South Korean firm. The first group of firms are the winners (the treated) in our winners vs. losers research design. The second group are the losers (the control). We construct pairs of winners and losers by matching each loser to a winner that is observationally similar and compare outcomes between these two groups. The identifying assumption is that the losers form a valid counterfactual for matched winners conditional on matched observables. We collect data about cancellations from historical contract documents. Our estimates imply that technology adoption increased adopters sales and revenue total factor productivity by 40–50%.

We also provide empirical evidence about local productivity spillovers of the adoption. The key identification challenge when estimating the spillovers is that spatially correlated shocks affect both firms' performance and their neighbors' adoption decisions (Manski, 1993). We deal with this challenge by exploiting spatial variation at a fine level of geographic detail. The median land area of our geographic unit of analysis is the size of Manhattan, or almost 34 square miles. Within each region and sector, we construct a spillover measure for each firm as the weighted average of local adopters of the same sector where the weight is given by the inverse of distance to other firms. This measure varies at the firm-level within each region and sector depending on firms' geographical proximity to adopters. We then regress non-adopters' sales and productivity on this spillover measure while controlling for time-varying region-sector fixed effects. Because we control for these fixed effects, our results are driven by variation in distances to adopters of the same sector within regions instead of being driven by variation across regions and sectors, so the usual regional or sectoral unobservables are not a concern in our empirical analysis. We find that non-adopters' sales and productivity grew faster when more neighboring firms had adopted foreign technology. Our estimates indicate that when the local share of adopters increased by a one percentage point, the sales and revenue TFP of non-adopters increased by 4–5%.

Third, we construct a dynamic spatial general equilibrium model with heterogeneous firms' technology adoption decisions and local productivity spillovers. We use the model to evaluate the general equilibrium effect of the South Korean government policy that temporarily subsidized technology adoption by heavy manufacturing firms. Firms' adoption decisions and the spillover endogenously shape comparative advantage and export patterns at the regional and national levels. Firms can adopt a more productive modern technology after incurring a fixed adoption cost. The spillover operates with a one-period lag, where the current local productivity increases in the local share of adopters in the previous period. This time lag of the spillover is a source of dynamics in the model. Because of this time lag, the share of adopters becomes a time-varying state variable. The spillover generates dynamic complementarity in firms' adoption decisions. A higher share of adopters in the previous period leads to higher gains from adoption that in turn induces more firms to adopt technology in the current period. Because adopters do not internalize this spillover, the amount of adoption is suboptimal. This justifies appropriate policy interventions that promote adoption.

In a simplified model, we show analytically that dynamic complementarity can lead to multiple steady states. When multiple steady states exist, they can be Pareto-ranked based on the equilibrium share of adopters. We label the steady states with low and high shares of adopters pre-industrialized and industrialized, respectively. In this model, an initial condition determines which steady state is realized in the long run. If an economy begins with a sufficiently large share of adopters, it converges to the industrialized steady state, but if not, it converges to the pre-industrialized steady state. This is because when an economy begins with a sufficiently large share of adopters, dynamic complementarity induces more firms to adopt technology, which in turn magnifies the strength of the complementarity in subsequent periods and vice versa. A temporary adoption subsidy can have permanent effects by moving an economy that was converging to the pre-industrialized steady state to a new transition path that converges to the industrialized steady state.

We calibrate the model to both micro and regional data. The model delivers structural equations that can be mapped to our reduced-form regression specifications. Thus, we can use the reduced-form estimates to identify two parameters that govern the direct productivity gains and the spillover. Subsidies are modeled as input subsidies. We do not observe the subsidies directly, but the model delivers an identifying moment for the subsidies: increases in shares of adopters during the periods when subsidies were available relative to the initial period when the subsidies were not provided. We show that this moment uniquely identifies the input subsidy under simplifying assumptions. The intuition behind this moment is that given information on the direct and spillover gains from adoption identified by our reduced-form estimates, the relative increases in shares of adopters are attributable to a reduction in adoption costs induced by the subsidies. We estimate the subsidy rate by fitting this moment. Finally, we identify a fixed adoption cost by the shares of adopters in the initial period when the subsidies were not provided.

Using the calibrated model, we ask how the pattern of industrialization in South Korea would have evolved had the government not provided subsidies. Our results show that if subsidies had not been provided, South Korea would have converged to a less industrialized steady state. In the steady state of this counterfactual economy, the heavy manufacturing sector's share of GDP would have decreased by a 15 percentage point lower, exports would have been 22.5 percentage points lower, and employment would have been 3 percentage points lower than the steady state of the baseline economy where subsidies had been provided. Also, the aggregate welfare would have been 10% lower. The aggregate differences are driven by a few regions that become more productive because of subsidy-induced technology adoption.

Related Literature. Our paper contributes to four strands of the literature. The first is the empirical literature that studies firm-level effects of industrial technology adoption in developing countries (e.g., Atkin et al., 2017; Juhász, 2018; Giorcelli and Li, 2021; Juhász et al., 2020; de Souza, 2021; Hardy and McCasland, 2021). Credible empirical evidence on firm-level effects of industrial technology in developing countries is scarce. We contribute to this literature by providing new empirical evidence on the direct productivity gains to adopters.

Second, this paper contributes to the empirical literature on local knowledge spillovers (see, among many others, Jaffe et al., 1993; Keller, 2002; Arzaghi and Henderson, 2008; Greenstone et al., 2010; Bloom et al., 2013; Kerr and Kominers, 2015; Kantor and Whalley, 2019; Moretti, 2021). While previous papers have focused on the local spillovers of R&D or innovation activities in developed countries, we provide new empirical evidence on local productivity spillovers of technology adoption in a developing country context and show that it was an important driving factor behind industrialization in South Korea.

Third, we contribute to the quantitative literature on multiple equilibria and the big push. According to the big push literature that dates to Rosenstein-Rodan (1943) and Hirschman (1958), underdevelopment results from complementarity and coordination failures (e.g., Murphy et al., 1989; Redding, 1996; Rodríguez-Clare, 1996; Ciccone, 2002; Kline and Moretti, 2014). We contribute to this literature by quantifying the aggregate consequences of coordination failure in firms' technology adoption decisions, multiple equilibria induced by this failure, and effects of the temporary subsidies provided by the South Korean government. While Crouzet et al. (2020) studied complementarity in technology adoption decisions of firms caused by network externalities and Buera et al. (2021) studied complementarity caused by higher intermediate intensities of the adoption goods, we study the local productivity spillovers of the adoption. The modeling framework of our paper is most closely related to that of Allen and Donaldson (2020) who study the role of history in determining spatial distribution of economic activity. Technology adoption choices are also determined by history in our model. Unlike the macroeconomic literature on barriers to technology adoption (e.g., Parente and Prescott, 1994; Comin and Hobijn, 2010; Cole et al., 2016), we study the coordination failure.

Finally, this paper contributes to the trade literature on the evolution of comparative advantage. Aggregate data show that comparative advantage evolves (Hausmann and Klinger, 2007; Hanson et al., 2015; Levchenko and Zhang, 2016; Schetter, 2019; Atkin et al., 2021), but the understanding of what drives this evolution has been limited so far.[6] Using detailed microdata, Pellegrina and Sotelo (2021) document how knowledge diffusion through migration shaped the comparative advantage of Brazil, and Arkolakis et al. (2019) study the role immigrants played in diffusing knowledge in the United States in the nineteenth century. We contribute to this literature by quantifying how technology adoption shaped South Korea's comparative advantage in heavy manufacturing sectors.

The rest of this paper is organized as follows. Section 1.2 describes the data we used for our empirical and quantitative analysis. Section 1.3 describes the historical background of South Korea's late industrialization and the South Korean government policy that promoted technology adoption. Section 1.4 presents reduced-form evidence on direct productivity gains to adopters and local productivity spillovers. In Section 1.5, we build the quantitative model. Section 1.6 describes how the model can be mapped to the data and reduced-form estimates. Section 1.7 presents quantitative analysis of the South Korean government policy. Section 1.8 concludes the paper.

1.2 Data

We construct our main dataset by merging firm balance sheet data with data on firms' technology adoption activities. We link these two datasets based on firms' names. The resulting dataset includes only firms in the manufacturing sectors. We classified firms into 10 manufacturing sectors, 4 of which are heavy manufacturing. The sample period of the constructed dataset is 1970 to 1982. The final dataset has 7,223 unique firms of which 49% are heavy manufacturing.

The final dataset includes 1,698 contracts made by 628 unique firms.[7] Of these,

[6]For theoretical works, see e.g., Krugman (1987) and Matsuyama (1992) for learning by doing and Buera and Oberfield (2020) and Cai et al. (2022) for knowledge diffusion.

[7]There were 1,776 contracts in total in the raw contract dataset. However, 78 of them could not be matched with

1,361 contracts and 457 firms were in heavy manufacturing sectors. Most of the adopted technologies were related to know-how about how to install or operate capital equipment or turnkey plants.[8] Firm balance sheet information is representative at the national level. On average, the dataset covers 75% of sectoral gross output from the input-output (IO) tables and 66% of the gross national output.[9] We describe our data construction procedure in Appendix Section A.1 in more detail.

Firm-Level Technology Adoption Contracts. We hand-collected and digitized firm-level data on technology adoption from official documents related to domestic firms' technology contracts with foreign firms from the National Archives of Korea and from the Korea Industrial Technology Association (1988). These documents had information about names of domestic and foreign contractors and contract years from 1966 to 1988. The law required domestic firms to submit related documents when they signed technology adoption contracts with foreign firms.[10]

Balance Sheet Data. We obtain firm balance sheet data by digitizing the Annual Reports of Korean Companies published by the Korea Productivity Center. Their publications cover firms with more than 50 employees. The data has information on sales, assets, fixed assets, and addresses of locations of establishments for the sample period between 1970 and 1982. Employment is not available until 1972. Using the addresses of plants and factories, we map firms' adoption activities to their location

our balance sheet data. This gives us 1,698 contracts.

[8]Specifically, about 74% of technology adoption contracts provided the know-how, 21.2% granted licenses, and 4% permitted the use of trademarks. For example, Appendix Figure A.1 is one page of the contract document between Kolon (South Korean) and Mitsui Toatsu (Japanese), both of which are chemical manufacturers. The contract shows that Mitsui Toatsu had to provide technical assistance and blueprints to Kolon.

[9]The ratio between the total sum of firm sales of the data and the gross output from the input-output tables is reported in Appendix Figure A.2. Also, see Appendix Table A.2 for descriptive statistics of the data.

[10]Any domestic firms' transactions with foreign firms, including technology adoption contracts, were strictly regulated under the Foreign Capital Inducement Act, which was first enacted in 1966. According to the law, once a domestic firm got approval from the government for the adoption, it had to report the related information to the Economic Planning Board that played a central role in the economic policy-making process in South Korea during the sample period.

of production. We convert addresses to the 2010 administrative divisions of South Korea.

1.3 Historical Background of Late Industrialization in South Korea

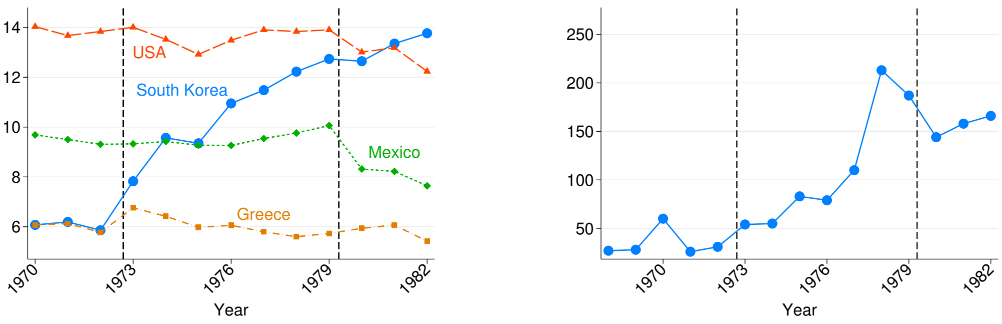
In late 1972, the South Korean government launched the Heavy and Chemical Industry (HCI) Drive to modernize and promote heavy manufacturing sectors, including chemicals, electronics, machinery, steel, non-ferrous metal, and transport equipment. One of the main policy instruments was subsidies for adopting foreign industrial technology.[11] In the 1970s, the adoption of foreign technologies and imported capital equipment related to those technologies were the main means of technology transfer from foreign developed economies to South Korea.[12]

The timing of the policy that subsidized technology adoption and the selection of the targeted sectors were driven by a political shock rather than economic conditions (Lane, 2019).[13] After the Vietnam War, President Nixon changed the diplomatic policy of the United States toward its East Asian allies. In the Nixon Doctrine (1969), he declared that the East Asian allies of the United States, including South Korea, should take primary responsibility for their self-defense instead of relying on the United States military. He also planned the complete withdrawal of the United States

[11] For example, Hyundai Motors, the largest automotive company in South Korea, did not have its own models until 1972. It merely reassembled the existing car model developed by Ford and imported most of the automobile parts. Hyundai Motors did not start to produce its own models until 1972, when it became possible because of technology adoption. In 1974, Hyundai Motors hired George Turnbull, the former director at British Leyland as a new vice-president in order to improve its management technology. In 1976, Hyundai Motors adopted engine technology from Perkins Engine, design from Ital Design, and transmission technology from Mitsubishi, which are British, Italian, and Japanese firms, respectively. The government subsidized Hyundai Motors to enable it to import new capital equipment and construct new turnkey plants related to the technologies it had adopted. See Choi and Levchenko (2021) for how the South Korean government subsidized firms during the 1970s.

[12] Another commonly used means of technology transfer in developing countries is the foreign direct investment (FDI) (Keller, 2004). In South Korea, however, FDI did not play a big role. The South Korean government strictly regulated FDI, and the total value of the technologies and capital equipment domestic firms imported was 22 times greater than that of FDI. Moreover, when compared to other developing countries, South Korea had a lower stock of FDI. For example, the value of South Korea's stock of FDI was only 7 percent of the value of Brazil's stock in 1983 (Kim, 1997, p.42-43).

[13] In Appendix Section A.2.2, we provide empirical evidence that supports this historical narrative of the political shock using an event-study specification. Also, see Choi and Levchenko (2021) and Kim et al. (2021) for further background on South Korea's HCI Drive.



A. Heavy mfg. share of GDP (%)

B. # of new foreign technology adoption contracts made by South Korean heavy mfg. firms, 1968-1982

Figure 1.1: Late Industrialization and Technology Adoption in South Korea

Notes. The two dotted vertical lines represent the start and end of the South Korean government policy that subsidized technology adoption from 1973 to 1979. We obtain data on heavy manufacturing's share of GDP across countries from the OECD's STAN Structural Analysis Database and the OECD National Accounts Statistics database.

military from South Korea. However, at this time, military tension between South and North Korea was rising. Because South Korea was heavily reliant on the United States military, the Nixon Doctrine posed a threat to the national defense of South Korea. In late 1972, in order to modernize South Korea's military forces and achieve self-reliant defense against North Korea, President Park of South Korea announced the drive to promote the heavy and chemical manufacturing sectors that are related to the arms industry.[14] The government considered South Korea's underdeveloped technology in heavy manufacturing sectors as one of the national threats.[15] Given South Korea's large technology gap with the world frontier, the government deemed technology adoption to be the most effective way to catch up with the frontier.[16] The HCI Drive was temporary because it ended in 1979 after President Park was assassinated.

The left panel of Figure 1.1 plots the GDP share of the heavy manufacturing

[14]At the same time, President Park declared martial law and amended the country's constitution into an authoritarian document, called the Yushin constitution, that extended his term of office.

[15]'Without rapidly improving our underdeveloped technology, our nation will be unable to secure an independent national defense system ... Inevitably, we will face a decline in our competitiveness of exports goods in international markets and national power, which bodes ill for our chance of a peaceful reunification with North Korea."

[16]"Considering our nations current technological state, adopting foreign advanced technologies and continuously adapting them to our needs seem to be the most effective catching-up strategy." (Ministry of Science and Technology, 1972, p. 4)

sector in South Korea and other selected economies. While at the beginning of the period of our analysis, South Korea's heavy manufacturing share was only 6%, it achieved a remarkable takeoff during the sample period, surpassing Mexico by the mid-1970s and the United States by 1982. The right panel plots the yearly number of new adoption contracts between South Korean and foreign firms. Our novel data reveals that the yearly number of contracts between South Korean and foreign firms for new technology quadrupled in the period between 1970 and 1982. This sudden and rapid increase in the rate of adoption coincided with temporary government subsidies for technology adoption in South Korea from 1973 to 1979.[17] Even after the policy ended in 1979, the South Korean economy continued to specialize in the heavy manufacturing sectors.

1.4 Empirical Evidence on Technology Adoption

In this section, we examine how technology adoption benefited South Korean firms. We provide econometric evidence on direct productivity gains for adopters and local productivity spillovers for non-adopters. According to the historical narrative, large-sized South Korean firms tend to rely on foreign sources to acquire advanced technologies, whereas small-sized firms relied on reverse engineering of technologies adopted by neighboring firms or on hiring experienced engineers from local adopters to obtain new technologies.[18] Our econometric evidence on the direct gains and local spillovers capture the former and the latter, respectively.

[17] In Appendix Figure A.5, we report heavy manufacturing's share of employment and export and the measure of revealed comparative advantage (Balassa, 1965). Consistent with Figure 1.1, the employment share increased from 4% to 9%, the export share increased from 13.5% to 35%, and the revealed comparative advantage measure rose from 0.2 to 0.65.

[18] See Kim and Kim (1985) and Kim (1997). For instance, during the 1970s, there were 15 firms producing black-and-white TV producers. The first four large firms started producing TV after adopting foreign technologies, but the other 11 acquired technologies by hiring experienced engineers from the first four adopters (Kim, 1997, p. 156). See A.3.4 for historical case studies.

1.4.1 Direct Productivity Gains to Adopters

Empirical Strategy: Winners vs. Losers Research Design. When estimating the direct productivity gains to adopters, one of the key econometric challenges is that the adoption decisions firms make are endogenous. Unobservable systematic differences between adopters and non-adopters may result in a spurious correlation between adoption status and adopters' performance, leading to the standard selection bias problem. An ideal empirical scenario would be a random assignment of adoption status across firms. To approximate an ideal random assignment, we implement a winners vs. losers research design, drawing on Greenstone et al. (2010) and Malmendier et al. (2018) that generate quasi-experimental variation in adoption status.

We define winners (the treated) as firms that successfully adopted technology from foreign firms. We define losers (the comparison) as non-adopters that made contracts with foreign firms that got approved by the government but were not able to adopt foreign technology because the foreign firm canceled the contract for reasons that had nothing to do with the South Korean firm. Examples include cancellations due to bankruptcy or to changes in the management team of the foreign firm. We exclude cancellations by domestic firms. The reasons for these cancellations include a domestic firm's sudden decreases in cash flow. See Appendix Figure A.3 for an example of a cancellation by a loser. When contracts were canceled after approval from the government, domestic firms had to report the related documents on the reason for the cancellation. We collect data on contract cancellations by reading thousands of historical documents from the archives.

After identifying losers, we match each loser with an adopter using the exact Mahalanobis matching algorithm. The matching proceeds in two steps. First, we exactly match on region and sector in order to absorb shocks within regions and sectors, such as market size or local wages. Second, within regions and sectors, we choose a winner that was most similar to a loser in terms of firm size measured by log assets, where the similarity is measured by the Mahalanobis distance. We match losers and winners with replacement, so we can match one winner to multiple losers in a given year if they were in the same sector and region. The matching procedure gives us 34 pairings among 57 unique firms. All the matched pairs consist of heavy manufacturing firms. See Appendix Section A.4.7 for more detail on the matching procedure.

Using the matched pairs of winners and losers, we estimate the following event study specification, which is a generalized difference-in-differences (diff-in-diffs) design where a matched winner adopted in different periods and a loser was the control group. For firm i of pair p in period t,

$$y_{ipt} = \sum_{\tau=\underline{T}}^{\bar{T}} \beta_\tau \times D_{pt}^{\tau} + \sum_{\tau=\underline{T}}^{\bar{T}} \beta_\tau^{diff} \times D_{pt}^{\tau} \times \mathbb{1}[Adopt_{it}] + \delta_i + \delta_p + \delta_t + \epsilon_{ipt}, \tag{1.1}$$

where i denotes firm, p pair, and t time. D_{pt}^{τ} are event-study variables defined as $D_{pt}^{\tau} := \mathbb{1}[t - \tau = t(p)]$, where $t(p)$ is event year of pair p.[19] $\mathbb{1}[Adopt_{it}]$ is a dummy variable for adoption status. δ_i, δ_p, and δ_t are firm, pair, and year fixed effects. ϵ_{ipt} is an error term. Dependent variables y_{ipt} are log sales, log revenue TFP estimated based on Wooldridge (2009), and labor productivity defined as value added per worker. Matching with replacement introduces mechanical correlation across residuals, because of the possible appearance of the same firm. Thus, we two-way cluster standard errors at the level of both firms and pairs. Appendix Section A.4.8 describes our revenue TFP estimation procedure in more detail.

[19] This specification is robust to possible issues of a staggered diff-in-diffs design with heterogeneous treatment effects. First, our event study specification allows for dynamic treatment effects. Second, 31 out of 34 losers did not adopt technology after the cancellation up to 5 years, so they can be considered as clean controls. Third, because we are controlling event dummies, we do not use past treated winners as controls.

Identifying Assumption. Our identifying assumption is that losers form valid counterfactuals for winners. For this assumption to hold, (i) losers and winners should be ex-ante similar in terms of both observables and unobservables prior to an event conditional on matched controls, and (ii) cancellations by foreign firms should be uncorrelated with domestic firms' unobservables.

Our matching procedure makes it likely that the first condition would hold. It ensures that losers and winners are well-balanced in terms of observable covariates. Also, because we are comparing winners and losers that both wanted to adopt technology, we are indirectly controlling for underlying unobservables that made these firms self-select into the adoption. Finally, although unobservable political favors or subsidies provided during the periods when subsidies were available could have affected firms' adoption decisions, we expect that winners and losers had a similar level of political favor from the government when they made contracts because our definition of losers required government-approved contracts.

Because we do not find differential pre-trends between winners and losers (which will be shown below), the second condition of our identifying assumption would be violated only by unobservable shocks that affected losers' performance after the event and were correlated with foreign firms' cancellations, but did not affect losers' performance before the event. One example would be a negative shock of losers at the time of the event that caused losers to be matched with a bad foreign contractor that experienced a change in its management teams or went into bankruptcy. We can directly test this using firm-to-firm structure of our technology adoption contract data. If our results are driven by matching based on negative shocks, we would expect the characteristics of foreign firms that made contracts winners and losers to be different.

Balance. To assess covariate balance between two groups, we report descriptive statistics of the matched pairs and covariate balance test results. The descriptive statistics (Appendix Table A.3) show that none of the t-statistics of tests that the mean of sales, employment, fixed assets, assets, and labor productivity of two groups are equal are statistically significant.[20] In Appendix Table A.4, we report the results of covariate balance tests where we estimate a linear probability model of the effects of pre-event firm observables on adoption status. Across all specifications, none of the estimated coefficients of firm observables are statistically different from zero both individually and jointly once we control for pair fixed effects. These results indicate that firm observables cannot predict the cancellations of losers, which supports our identifying assumption that cancellations by foreign firms were exogenous shocks to domestic firms.

We compare two groups of foreign firms that made contracts with winners and losers based on their patenting activities in the United States. We obtain data on patenting activities in the United States from the United States Patent and Trademark Office (USPTO). We use firms' patenting activities in the United States as a proxy for how these firms are close to the world technology frontier. When these foreign firms made contracts, Appendix Table A.5 shows that none of the t-statistics of tests that various measures of patent activities of two groups are equal are statistically significant. This rules out an alternative story that negative shocks made losers be matched with bad foreign firms.

Baseline Results. Table 1.1 and Figure 1.2 report the estimated coefficients in Equation (1.1). There are no pre-trend. Winners' sales, revenue TFP, and labor produc-

[20] Both winners and losers were larger than the average of all heavy manufacturing firms. For example, the average log sales of all heavy manufacturing firms were 15.54, but the averages of winners of losers were 17.80 and 18.46, respectively (column (2) of Appendix Table A.2). Therefore, non-adopters may not represent a valid counterfactual for adopters, and naive comparison between them may lead to biased estimates.

tivity did not begin to increase until adoptions occurred. 4 years after the adoption, winners' sales, revenue TFP, and labor productivity increased by 47%, revenue TFP by 42%, and labor productivity by 62%, and these effects were persistent.

Robustness. Increases in firms' sales or revenue TFP measures may reflect increases in demand shocks or mark-ups of the domestic market rather than productivity (Syverson, 2011). To deal with this issue, we merge our data set with KIS-VALUE that covers firms' export data after 1980. We find that the winners were 29 percentage points more likely to be an exporter and increased amounts of exports 7 or 8 years after the event when compared to the losers. These increases in exports in foreign markets are unlikely to be driven by demand shocks or mark-ups of the domestic market. See Section A.4.3 for more detail.

We compare our estimates from the winners vs. losers research design to estimates from a standard two-way fixed effects event study design that does not correct the selection problem. We find that the estimates from the standard event-study design is downward biased.[21] The magnitude of the estimated coefficients from the standard event-study design is roughly 50% smaller than our estimates. This shows that correcting the selection problem is important for understanding the impact of technology adoption. See Appendix Section A.4.4 for more detail.

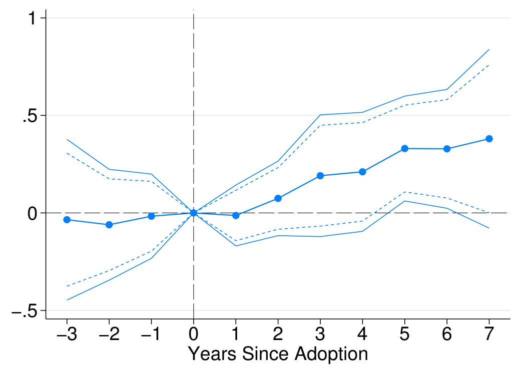
We run the same regressions using different revenue TFP measures based on Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS. The results are reported in Appendix Figure A.8 and columns (4)-(6) of Table 1.1. Even though we use different measures, the estimated event study shows no pre-trend, and the estimated coefficients are within a standard error of the estimates of column (3) of

[21] One possible scenario that leads to the downward bias is subsidies based on political favors. If subsidies were targeted to firms that are politically connected but less productive, this may result in the downward bias. However, the winners vs. losers research design can correct this selection problem, because winners and losers got the approval from the government, implying that they may had similar level of political favors.

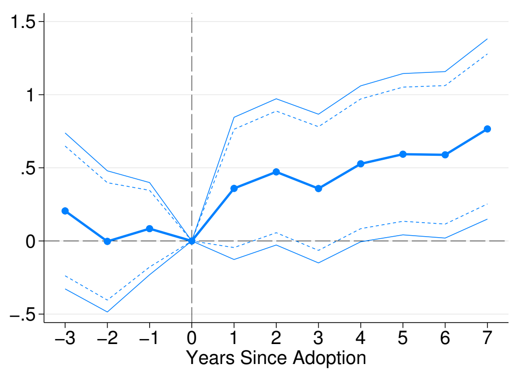
Table 1.1: Event Study Estimates of Direct Productivity Gains to Adopters: Winners vs. Losers Research Design

Research Design	Winners vs. losers					
Dep. Var.	Log sales	Log labor productivity	Log revenue TFP			
			W. (2009)	ACF (2015)	LP (2003)	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
3 years before event	0.00	–0.09	0.01	0.06	0.04	0.00
	(0.27)	(0.41)	(0.24)	(0.30)	(0.24)	(0.29)
2 years before event	0.07	–0.36	–0.11	–0.18	–0.08	–0.19
	(0.24)	(0.46)	(0.24)	(0.34)	(0.24)	(0.34)
1 year before event	–0.10	–0.02	0.04	0.10	0.06	0.08
	(0.12)	(0.23)	(0.15)	(0.19)	(0.15)	(0.19)
Year of event						
1 year after event	0.31	0.28	0.22	0.37	0.23	0.33
	(0.25)	(0.41)	(0.37)	(0.38)	(0.37)	(0.39)
2 years after event	0.53*	0.64**	0.56**	0.71**	0.56**	0.67**
	(0.27)	(0.30)	(0.26)	(0.30)	(0.26)	(0.29)
3 years after event	0.47*	0.62**	0.41*	0.66**	0.43*	0.63**
	(0.26)	(0.29)	(0.23)	(0.28)	(0.23)	(0.27)
4 years after event	0.48**	0.62**	0.42*	0.67**	0.45**	0.63**
	(0.23)	(0.27)	(0.21)	(0.25)	(0.21)	(0.24)
5 years after event	0.58**	0.43	0.52**	0.64**	0.52**	0.57*
	(0.26)	(0.36)	(0.21)	(0.29)	(0.23)	(0.29)
6 years after event	0.54*	0.55*	0.46**	0.59**	0.46*	0.56**
	(0.29)	(0.28)	(0.23)	(0.29)	(0.24)	(0.27)
7 years after event	0.66**	0.56*	0.57**	0.69**	0.58**	0.67**
	(0.31)	(0.32)	(0.23)	(0.29)	(0.23)	(0.28)
Firm FE	✓	✓	✓	✓	✓	✓
Pair FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Adj. R^2	0.88	0.61	0.86	0.94	0.90	0.60
# cluster (pair)	34	34	34	34	34	34
# cluster (firm)	57	57	57	57	57	57
N	951	835	827	827	827	827

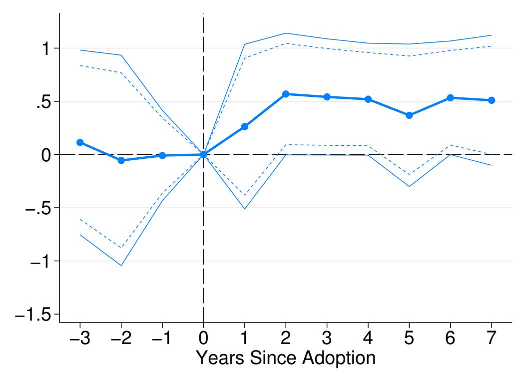
Notes. This table reports the estimated event study coefficients β_τ^{diff} in Equation (1.1) based on the winners vs. losers research design. β_0^{diff} is normalized to zero. The dependent variables are log sales, log revenue TFP, and log labor productivity defined as value added divided by employment. Value added is obtained as sales multiplied by the value added shares obtained from input-output tables corresponding to each year. In columns (3), (4), (5), and (6), we estimate log revenue TFP based on Wooldridge (2009), Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS, respectively. All specifications control for event time dummies, firm fixed effects, pair fixed effects, and calendar year fixed effects. Robust standard errors in parenthesis are two-way clustered at the pair and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.



A. Log sales



B. Log revenue TFP



C. Log labor productivity

Figure 1.2: Direct Productivity Gains to Adopters: Winners vs. Losers Design

Notes. This figure illustrates the estimated β_τ^{diff} in Equation (1.1) based on winners vs. losers research design. In Panels A, B, and C, the dependent variables are log sales, revenue TFP, and labor productivity. We estimate revenue TFP based on Wooldridge (2009). Labor productivity is defined as value added per worker. β_0^{diff} is normalized to be zero. All specifications control for event time dummies, and firm, pair, and calendar year fixed effects. The plotted coefficients correspond to columns (1)-(3) of Table 1.1. The figure reports 90 and 95 percent confidence intervals based on standard errors two-way clustered at the levels of pairs and firms.

Table 1.1.

1.4.2 Local Productivity Spillovers to Non-Adopters

In this subsection, we provide empirical evidence on local productivity spillovers of the adoption. Our measure for the spillover is a weighted mean of the local adoption status of firms within the same sector, where the weight is given by the inverse of distance between firms. We define the spillover experienced by firm i in region n and sector j at time t as follows:

$$\text{Spill}_{inj(t-h)} = \sum_{k \in nj/\{i\}} \left\{ \frac{(1/dist_{ik})\mathbb{1}[\text{Adopt}_{knj(t-h)}]}{\sum\limits_{k' \in nj/\{i\}} (1/dist_{ik'})} \right\}, \tag{1.2}$$

where $nj/\{i\}$ is a set of sector j firms in region n excluding firm i, $dist_{ik}$ is the distance between firms i and k, and $\mathbb{1}[\text{Adopt}_{knj(t-h)}]$ is a dummy variable for firm k's adoption status lagged by h years. Lagging the variable allows for the possibility that it took some time for new knowledge from adopted technologies to diffuse locally. When we construct the spillover measure for firm i, we exclude firm i to rule out mechanical correlation. For our baseline specification, we set the value of h as 4 and conduct robustness checks for different values of h. Each firm within the same region and sector has different values for spillover depending on its distance from adopters. Distance from adopters is the main variation we use for our empirical analysis.

The spillover measure can be interpreted as the probability that firm i's manager would meet other managers who worked in firms that had adopted foreign technologies. Each manager is endowed with a unit of time and can randomly meet at most one manager from other firms. The probability that a manager would meet a manager from firm k is given by the inverse of the distance between firms i and k. The inverse of the distance is a proxy for spatial frictions that would have impeded local interaction between managers of two firms.[22] The spillover measure captures the fact that knowledge spillovers are highly localized and quickly decay with distance. This is supported by the recent empirical evidence on knowledge spillovers (e.g., Jaffe et al., 1993; Kerr and Kominers, 2015; Kantor and Whalley, 2019; Moretti, 2021).

Using this spillover measure, we consider the following fixed effect regression model:

$$y_{injt} = \beta^S \text{Spill}_{inj(t-4)} + \delta_i + \delta_{njt} + \epsilon_{injt}, \tag{1.3}$$

where i denotes firm, j sector, n region, and t time. δ_i represent time-invariant firm fixed effects and δ_{njt} represent time-varying region-sector fixed effects. We use log sales and revenue TFP as dependent variables (y_{injt}). δ_i absorb time-invariant firm factors and δ_{njt} absorb time-varying shocks within each region and sector.

To difference out firm fixed effects, we estimate Equation (1.3) in long-difference:

$$\triangle y_{injt} = \beta^S \triangle \text{Spill}_{inj(t-4)} + \gamma y_{injt_0} + \mathbf{X}'_{injt_0}\boldsymbol{\beta} + \triangle \delta_{njt} + \triangle \epsilon_{injt}, \tag{1.4}$$

where $\triangle$ is a time difference operator. All specifications include the initial dependent variable y_{injt_0}. The baseline sample includes firms that were operating before 1973 and after 1979 and did not adopt foreign technologies between these periods. $\mathbf{X}_{injt_0}$ are firm controls measured at the initial sample period, which allows for heterogeneous trends that depend on firm observables. Standard errors are two-way clustered at the levels of regions and conglomerates. In South Korea, large conglomerate groups known as chaebols own multiple firms across sectors and regions. Clustering at the

[22] By taking the weighted average, we implicitly assume that the spillover measure is invariant to the total number of firms. As far as we know, there is no consensus about the functional form of knowledge spillovers (Combes and Gobillon, 2015; Gibbons et al., 2015). However, we think the weighted average is more suitable in our setting. First, this is consistent with our theoretical interpretation, which is also widely adopted in growth and knowledge diffusion literature (Jovanovic and Rob, 1989; Lucas and Moll, 2014; Buera and Oberfield, 2020; Perla and Tonetti, 2014; Perla et al., 2021). Given that managers' time is a limited resource in the real world, this theoretical interpretation seems to be more natural than an alternative scenario where a manager can interact with all firms in the same local area. In this scenario, the spillover varies depending on the total number of adopters rather than the shares. Second, the literature on externalities has commonly used averages to capture agglomeration forces, such as share of skilled labor (Moretti, 2004) and population density (Ciccone and Hall, 1996).

conglomerate level allows for arbitrary correlation of error terms between firms within the same conglomerate group.

To use the data more efficiently, we use overlapping 8-year long-differences: 1971-1979 and 1972-1980. Each set covers the period between 1973 and 1979 when the temporary subsidies were provided. Because we cluster firms at both region and conglomerate level, this is innocuous. We add dummies for each set of differences and for interaction terms between these dummies and δ_{njt}.

Identifying Assumption. Our identifying assumption for a causal interpretation is that distance to adopters within regions and sectors ($\text{Spill}_{inj(t-4)}$) is uncorrelated with the error term ϵ_{injt} conditional on δ_{njt}, δ_i, and other controls. There are two main identification concerns highlighted by Manski (1993). First, neighborhood shocks within regions and sectors that are correlated across firms can affect both firm i's outcomes and the adoption decisions of neighboring firms, leading to spurious correlation. Second, adopters tend to be larger than non-adopters and omitting other effects of being close to large firms can lead to omitted variable bias.

We deal with the first concern by controlling for time-varying region-sector fixed effects at a fine level of geographic detail. The median size of our geographical unit of analysis for the sample is about Manhattan-sized, or almost 34 square miles. This is much finer than the unit of analysis in many previous studies. Our identifying variation comes purely from distance to adopters within the same sector and region, but not from variation across regions or sectors. Variation in $\text{Spill}_{inj(t-4)}$ mainly comes from two sources: (i) adoption decisions by non-adopters operating at the start of the sample period, and (ii) entry and adoption decisions of new firms entering between the start and the end of the sample period.[23] Because we control for δ_{njt} and

[23]The firms that enter began production between the start and the end of the sample period affected the spillover

difference out δ_i, neighboring firms' adoption decisions based on time-varying region-sector factors do not bias our estimates. Only adoption or entry decisions based on time-varying firm-specific factors that are spatially correlated at the neighborhood level would bias our estimates. For example, infrastructure improvement at the neighborhood level that affected both firms' outcomes and adoption decisions would bias our estimates. Exploiting spatial variation at a fine level mitigates potential spatial correlation at the neighborhood level within each region and sector.

We deal with the second concern by isolating variation in proximity to adopters from proximity to large firms by controlling for other potential means of local spatial interactions between firms. We control for the average sales of local firms by inversely weighting distances:

$$\ln\Big(\text{Spill-Sales}_{injt}\Big) = \ln\left(\sum_{k\in nj/\{i\}}\left\{\frac{(1/dist_{ik})\text{Sales}_{kt}}{\sum\limits_{k'\in nj/\{i\}}(1/dist_{ik'})}\right\}\right). \tag{1.5}$$

This weighted average sale proxies other agglomeration or competition forces of being close to large firms within the same region and sector. We also control for a measure of access to local markets attributable to local input sourcing by taking the weighted sum of neighbors' sales period t input-output coefficients, where the weight is given by the inverse of the distances (Donaldson and Hornbeck, 2016):

$$\ln\Big(\text{Input-MA}_{injt}\Big) = \ln\left(\sum_{j'}\sum_{k\in nj'/\{i\}}\gamma_j^{j'}(1/dist_{ik})\text{Sales}_{kt}\right), \tag{1.6}$$

where $\gamma_j^{j'}$ represent shares of sector j' intermediate inputs used by sector j. This measure of market access is a proxy for differential market size attributable to localized input sourcing. Because we do not have information on commodity or service sector firms, we sum j' only across manufacturing sectors.

measure of firms that were in production at the beginning of the sample period, but we did not include them in the sample because we restrict the sample to firms that were operating at the start of the period.

Table 1.2: Local Productivity Spillovers from Technology Adoption

Dep. Var.	Log sales					Log revenue TFP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Never-Adopter Sample									
Spill	4.39***	3.79**	4.94***	4.23***	4.07**	5.55***	5.41***	5.81***	5.34***	5.11**
	(1.54)	(1.64)	(1.70)	(1.50)	(1.76)	(1.84)	(1.62)	(2.08)	(1.78)	(1.92)
ln(Spill-Sales)			–0.02		–0.02			–0.02		–0.01
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.03	–0.02				–0.04**	–0.03
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.18	0.22	0.19	0.19	0.22	0.44	0.42	0.44	0.44	0.42
# clusters (region)	53	53	53	53	53	41	36	41	41	36
# clusters (conglomerate)	636	630	636	636	630	324	275	324	324	275
N	1079	1073	1079	1079	1073	344	292	344	344	292
	Panel B: Full Sample									
Spill	4.23***	3.93***	4.45***	3.86***	3.72**	4.75***	3.99**	4.72***	4.45***	3.44*
	(1.18)	(1.43)	(1.31)	(1.19)	(1.52)	(1.63)	(1.90)	(1.73)	(1.58)	(1.82)
$\mathbb{1}[Adopt]$	0.32**	0.26	0.32**	0.31**	0.25	0.15*	0.14	0.15*	0.14	0.12
	(0.15)	(0.20)	(0.15)	(0.15)	(0.19)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)
ln(Spill-Sales)			–0.01		–0.01			0.00		0.00
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.05***	–0.04*				–0.05***	–0.05**
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.19	0.24	0.19	0.19	0.24	0.37	0.43	0.37	0.38	0.43
# clusters (region)	54	54	54	54	54	45	41	45	45	41
# clusters (conglomerate)	702	697	702	702	697	381	338	381	381	338
N	1264	1259	1264	1264	1259	431	387	431	431	387
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag the adoption status of firms by four years. In Panel A, we use the subsample that include only firms that did not adopt any technology during the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adoption status. The dependent variables are log sales in columns (1)-(5) and revenue TFP in columns (6)-(10). We estimate revenue TFP based on Wooldridge (2009). The additional controls ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and for the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Baseline Results. Table 1.2 reports the OLS estimates for β^S. Column (1) of Panel A is our baseline estimate.[24] The estimated coefficient is statistically significantly positive. One standard deviation increase in the spillover contributes to 14.5% increases in sales.[25] β^s can also be interpreted as a semi-elasticity of non-adopters' sales to local shares of adopters in a hypothetical region when all firms are equally distanced. In this interpretation, a one percentage point increase in the local share of adopters leads to a 4.39% increase in non-adopters' sales in the hypothetical region. In columns (2), (3), and (4), we also control for conglomerate fixed effects, ln(Spill-Sales), and ln(Input-MA), respectively.[26] In column (5), we control for all other variables. The estimates with additional controls all stay within a standard error of the baseline estimate. The estimated coefficients of ln(Spill-Sales) and ln(Input-MA) are not statistically significant and do not take positive values.[27] In columns (6)-(10), we use log revenue TFP as a dependent variable.[28] The estimates for log revenue TFP are about 20% larger than the estimates for log sales.

In Panel B, we run the same regression for the full sample, including both adopters and non-adopters. For the full sample, we control for a dummy variable for own adoption status. Because they are likely to be correlated with the error term, we do not meaningfully interpret this variable. The estimates based on the full sample are

[24] The magnitude of the estimated coefficients is consistent with the estimates in the literature on local knowledge spillover. The estimates in column (1) of Panel A indicate that the elasticity of firms' sales to the spillover at the mean and the 90th and 95th percentiles is 0.05, 0.13, and 0.26, respectively. We calculate the elasticity of the adoption spillover as follows. The mean level of the local share of adopters is 0.011. An increase of 1% of the mean level (0.00011) increases firms' sales by 0.05% (= $100 \times 0.00011 \times 4.39$). The elasticities at the 90th and 95th percentiles are calculated similarly. For example, estimates from Bloom et al. (2013) imply that the elasticity of firms' sales to their spillover measure based on patents is 0.19–0.26. We calculate elasticity above the 90th percentile because shares of adopters are highly skewed; where the 75th, 90th, 95th, and 99th percentiles were 0, 0.03, 0.06, and 0.18, respectively.

[25] This is calculated as $14.5 = 100 \times 0.033 \times 4.39$, where 0.033 is one standard deviation of the adoption spillover.

[26] When we control for the fixed effects of conglomerates, we categorize independent firms into one single group.

[27] One potential explanation for the null results of ln(Spill-Sales) and ln(Input-MA) is that knowledge spillovers decay more quickly with distances than other spatial interactions captured by the other two controls, and the other two spatial interactions operate at a broader spatial scale than knowledge spillovers. Then, conditional on δ_{njt}, ln(Spill-Sales) and ln(Input-MA) will not have significant results.

[28] The number of samples for revenue TFP was smaller because employment data was not available until 1972. We use only one set of differences between 1972 and 1980.

within a standard error of the baseline estimates in column (1) of Panel A.

Robustness. We provide a battery of robustness checks. Instead of using the spillover measure with a four year lag, we use the spillover measure with three or five year lags. The results are reported in Appendix Tables A.6 and A.7. The estimated coefficients from these robustness checks remain within a standard error of the baseline estimates.

It is possible that the local spillovers were operating at a broader level than our geographical unit of analysis. To check this, we aggregate our geographical unit to 42 regions based on industrial structure and electoral districts. We define the spillover similarly to Equation 1.2 at the broader regional level. Then, we run the same regression while controlling the same set of region and sector fixed effects with the baseline specification. Thus, we absorb the same time-varying shocks with the baseline specification while allowing the spillovers to operate at the broader level. We two-way cluster at the broader regional level and the conglomerate level. The results are reported in Appendix Tables A.8. The estimated coefficients remain within a standard error of the baseline estimates.

We consider cross-sector spillovers. Following Ellison et al. (2010) and Hanlon and Miscio (2017), we construct the local cross-sector spillover measure based on the expression in Equation (1.2) and the input-output table coefficients. We do not find statistically significant results for the local cross- sector spillovers. See Appendix Section A.4.5 for more detail.

Instead of using log sales or revenue TFP, we use log fixed assets, assets, and employment, labor productivity. The results are reported in Appendix Tables A.9 and A.10. The estimated coefficients are statistically significant and are positive for different dependent variables except for employment.

Instead of using $(1/dist_{ik})$, we also consider alternative weights $(1/dist_{ik}^{\alpha})$ for Input-MA$_{injt}$ where $\alpha = 1.1$, which is the value of the average coefficient based on a meta-analysis performed by Head and Mayer (2014). The results are reported in Appendix Table A.11.

1.5 Theoretical Framework

In this section, we present a dynamic spatial model with firms' endogenous adoption decisions and local productivity spillovers.

1.5.1 Setup

We consider a small open economy Home with N regions and J sectors. We divide the world into Home and Foreign. We assume that Home is small and it cannot affect Foreign aggregates. However, its domestic prices are determined by domestic supply and demand conditions, and Home firms face downward sloping demands from Foreign.[29] Subscripts $n, m \in \mathcal{N}$ index Home regions, and $j, k \in \mathcal{J}$ sectors, where $\mathcal{N}$ and $\mathcal{J}$ are the sets of Home regions and sectors. Time is discrete and indexed by $t \in \{1, 2, \ldots\}$.

There are two types of goods: intermediate and final goods. Intermediate goods are produced by intermediate goods producers. There is a fixed mass of firms (M_{nj}) in each region and sector. Sectors are either tradable $(j \in \mathcal{J}^x)$ or non-tradable $(j \notin \mathcal{J}^x)$. For $j \in \mathcal{J}^x$, intermediate goods are tradable across regions and can be exported to Foreign. Both internal and international trade of sector j are subject to iceberg trade costs $\tau_{nmj} \geq 1$ and $\tau_{nj}^x \geq 1$, respectively. When exporting to Foreign, firms additionally incur fixed export costs (Melitz, 2003). In a subset of sectors $(\mathcal{J}^T \subset \mathcal{J})$, firms in these sectors can adopt advanced technology from foreign sources

[29] The small open economy setup of our model is similar to that of Bartelme et al. (2021).

after incurring fixed adoption costs.

In each region, there is a competitive labor market. We normalize the total population of the Home regions to 1: $L_t = \sum_{n \in \mathcal{N}} L_{nt} = 1$, where L_{nt} is population in region n.

1.5.2 Firms

Production. Each intermediate variety is produced by intermediate goods producers, which we call firms. Each firm is indexed by subscript i. Firms are heterogeneous in productivity. Firm i's output y_{it} is

$$y_{it} = z_{it} L_{it}^{\gamma_j^L} \prod_{k \in \mathcal{J}} M_{it}^{\gamma_j^k}, \qquad \gamma_j^L + \sum_{k \in \mathcal{J}} \gamma_j^k = 1, \tag{1.7}$$

where z_{it} is firm i's productivity, L_{it} are labor inputs, M_i^k are sector k intermediate inputs, and γ_j^k are Cobb-Douglas shares. A unit cost of an input bundle is $c_{njt} = (w_{nt}/\gamma_j^L)^{\gamma_j^L} \prod_{k \in \mathcal{J}} (P_{nkt}/\gamma_j^k)^{\gamma_j^k}$, where w_{nt} is wage and P_{njt} is a price of intermediate inputs.

In each region and sector, a final goods producer produces nontradable local sectoral aggregate goods used for final consumption and for intermediate inputs. They are perfectly competitive. A final goods producer aggregates all available varieties from all regions and countries using a constant elasticity of substitution (CES) aggregator:

$$Q_{njt} = \left[\sum_{m \in \mathcal{N}} \int_{\omega \in \Omega_{mj}} q_{it}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \int_{\omega \in \Omega_j^f} q_{it}^f(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}. \tag{1.8}$$

Q_{njt} are the quantities of local aggregate sectoral goods produced. Ω_{mj} is the set of available sector j varieties in region m. q_{it} and q_{it}^f are the quantities demanded of an intermediate variety ω produced by a domestic and a foreign firm, respectively. We assume that the available set of foreign varieties Ω_j^f is exogenously given to the

Home regions and is the same across regions. Because there are no fixed export costs for internal trade, each region faces the same set of available varieties.

The exact CES price index is

$$P_{njt}^{1-\sigma} = \sum_{m \in \mathcal{N}} \left[\int_{\omega \in \Omega_{mj}} p_{it}(\omega)^{1-\sigma} \right] + (\tau_{nj}^{x})^{1-\sigma} \underbrace{\int_{\omega \in \Omega_j^f} p_{it}^f(\omega)^{1-\sigma}}_{=(c_{jt}^f)^{1-\sigma}}, \tag{1.9}$$

where p_{it} is the price of Home variety and p_{it}^f is a FOB price of an imported variety from Foreign. Because we have assumed a small open economy, Home takes the FOB prices of foreign firms as given and therefore c_{jt}^f is exogenous to Home.

Technology Adoption and Exports. In each period, firms make two static decisions: (i) whether to adopt advanced technology and (ii) whether to export. Both adopting technology and exporting incur adoption and export fixed costs in units of input bundles (F_j^T and F_j^x). The fact that both adoption and export costs are fixed costs make firms' decisions static. This static nature of firms' problems makes the model computable while preserving rich cross-sectional regional heterogeneity, and connecting the model to the data and econometric estimates.[30] Once firms decide to adopt technology and pay fixed adoption costs, they can increase their productivity (Yeaple, 2005; Lileeva and Trefler, 2010; Bustos, 2011).[31]

Firm productivity z_{it} is composed of three terms:

$$z_{it} = \underbrace{\eta^{T_{it}}}_{\substack{\text{Direct} \\ \text{productivity gains}}} \times \underbrace{f(\lambda_{njt-1}^T)}_{\substack{\text{Local} \\ \text{spillover}}} \times \underbrace{\phi_{it}}_{\substack{\text{Exogenous} \\ \text{productivity}}},$$

[30] For example, see Desmet and Rossi-Hansberg (2014), Desmet et al. (2018), and Caliendo et al. (2019) for forward-looking agents.

[31] F_j^T is a reduced-form parameter that includes direct payment to foreign sources, the costs of installing a new structure or capital equipment related to a newly adopted technology, and any barriers to adoption. Many previous papers have studied sources of adoption barriers in developing countries (see, among many others, Parente and Prescott, 1994; Banerjee and Duflo, 2005; Acemoglu et al., 2007; Atkin et al., 2017). Also, South Korea's political context in the 1970s might have affected F_j^T. Due to the Cold War, the United States government wanted the South Korean economy to be self-sustaining and promoted South Korea's economic growth. Therefore, it did not block transfers of technology to South Korean firms (Vogel, 1991, p.8).

where $\eta > 1$ is direct productivity gains from adoption, T_{it} is a binary adoption decision, $f(\lambda^T_{njt-1})$ is a local adoption spillover that increases in the share of adopters in the previous period λ^T_{njt-1}, and ϕ_{it} is exogenous productivity. We allow the spillover to operate with a one-period lag (Allen and Donaldson, 2020), which is more realistic given that our focus is the transformation of the South Korean economy within 10 years instead of the long-run outcomes that have been studied more frequently in the trade literature.[32] When making adoption decisions, adopters internalize the direct productivity gain η but not the spillover $f(\lambda^T_{njt-1})$. These externalities mean that social returns to adoption are larger than private returns. This leads to adoption rates that are lower than the socially optimum level. Because of firms' endogenous technology adoption decisions, z_{it} is endogenously determined in the equilibrium.[33] For sectors where technology adoption is not available ($j \notin \mathcal{J}^T$), firms' productivity consists of only exogenous productivity: $z_{it} = \phi_{it}$.

$f(\lambda^T_{njt-1})$ captures local knowledge spillovers from newly adopted technologies. We parametrize $f(\lambda^T_{njt-1})$ as follows:

$$f(\lambda^T_{njt-1}) = exp(\delta\lambda^T_{njt-1}),$$

where $\delta > 0$ is the semi-elasticity of firm productivity with respect to a local share of adopters. Under this parametrization, we show that δ can be mapped to the reduced-form spillover estimate in Section 1.4.2. The spillover can be micro-founded based on (1) local diffusion of new engineering knowledge; and (2) learning externalities and labor mobility across firms. These two sets of microfoundations are based on

[32] Allowing the spillover to operate with a lag gives an economy a deterministic static equilibrium in each period (Adserà and Ray, 1998). This is a desirable theoretical property for two reasons. First, we can rule out unrealistic situations where an economy swings from one equilibrium to another in a different period depending on agents' self-fulfilling beliefs. See Krugman (1991) and Matsuyama (1991) for further discussion of self-fulfilling beliefs. Second, because there is a unique static equilibrium for each period, the model can be easily mapped to cross-sectional data. In general, multiple static equilibria models suffer from identification issues due to multiplicity (Jovanovic, 1989). Kline and Moretti (2014) and Allen and Donaldson (2020) also allowed agglomeration to operate with some lags.

[33] Recent studies (see, among many others, Desmet and Rossi-Hansberg, 2014; Desmet et al., 2018; Walsh, 2019; Nagy, 2020; Peters, 2021) also present dynamic spatial model with endogenous local productivity. Unlike these studies, local productivity is endogenously determined because of firms' technology adoption decisions in our model.

historical case studies of South Korea in the 1970s.[34] Complete derivations of the microfoundations and related historical cases are described in Appendix A.3.4.

ϕ_{it} is drawn from a distribution $G_{njt}(\phi)$, which varies across regions, sectors, and periods. Each draw is independent across firms, regions, sectors, and time. We assume that exogenous productivity ϕ_{it} follows a bounded Pareto distribution (Chaney, 2008; Helpman et al., 2008):

$$\phi_{it} \sim \frac{1-(\phi_{it}/\phi_{njt}^{min})^{-\theta}}{1-(\phi_{njt}^{max}/\phi_{njt}^{min})^{-\theta}},$$

which is parametrized by ϕ_{njt}^{max}, ϕ_{njt}^{min}, and θ. We also assume that the gap between the lower and upper bounds of the distribution is the same across regions, sectors, and periods: $\phi_{njt}^{max} = \kappa\phi_{njt}^{min}$, parametrized by κ. The lower bound of the distribution may vary across regions, sectors, and periods, but the upper bound is always proportional to the lower bound by κ. This distributional assumption gives us analytical expressions for aggregate variables and rationalizes zeros observed in the data.[35]

Adoption Subsidy. We model the adoption subsidies in Section 1.3 as input subsidies because the South Korean government provided subsidies to large adopters so they could purchase intermediate inputs and new capital equipment related to the technologies they adopted. Adopters are potentially eligible for input subsidies $0 < s_{njt} < 1$ that can vary across regions, sectors, and periods. Therefore, firm i's unit cost of production, $\tilde{c}_{it}$, is $\frac{c_{njt}}{\phi_{it}f(\lambda_{njt-1}^{T})}$ if firm i adopts technology or $\frac{1-s_{njt}}{\eta} \times \frac{c_{njt}}{\phi_{it}f(\lambda_{njt-1}^{T})}$ if

[34] The historical evidence shows that new ideas and knowledge about adopted technologies were frequently transmitted to local capital goods producers through reverse engineering of capital equipment related to adopted technologies. Also, technical personnel of adopters moved frequently to other firms and their movement played an important role in diffusing knowledge about adopted technologies. It is further supported by higher aggregate labor mobility rates in South Korea in the 1970s than those of Japan and the United States (Kim and Topel, 1995). Also, learning externalities and knowledge spillovers through labor mobility have been widely studied in the literature. For example, see Lucas (1988) for learning externalities of human capital; see Stoyanov and Zubanov (2012) and Serafinelli (2019) for empirical evidence on the effects of labor mobility across firms on knowledge diffusion.

[35] If $\kappa \to \infty$, the bounded Pareto distribution becomes unbounded Pareto. However, the unbounded Pareto distributional assumption cannot rationalize zeros because as productivity is unbounded, there is always a small share of firms that adopt technology regardless of the values of F_j^T. Helpman et al. (2008) also uses a bounded Pareto distributional assumption to rationalize zero trade flows across countries.

it did not. Adopters have a lower unit cost of production than non-adopters because of higher productivity (η) and input subsidies (s_{njt}).

The government imposes a labor tax (τ_t^w) to finance these subsidies.[36] We assume that the labor tax rate is constant across regions, so the after-tax wages in region n are $(1-\tau_t^w)w_{nt}$. The government budget is balanced every period.

A Firm's Maximization Problem. Each firm faces a CES demand and is monopolistic for its own variety. Firm i's quantities demanded from region m are $q_{inmjt} = (\tilde{p}_{it})^{-\sigma} P_{mjt}^{\sigma-1} E_{mjt}$ and when firm i charges price $\tilde{p}_{it}$. The demanded from foreign markets at that price is $q_{injt}^x = (\tilde{p}_{it})^{-\sigma} D_{jt}^f$. A firm optimally charges a constant mark-up $\mu = \sigma/(\sigma-1)$ over its marginal cost. Thus, the prices charged by firm i in region n of sector j charged to buyers in region m are $p_{inmjt} = \mu \tau_{nmj} \tilde{c}_{it}$ and export prices are $p_{injt}^x = \mu \tau_{nj}^x \tilde{c}_{it}$.

A firm's profit is obtained after maximizing over T_{it} and x_{it}:

$$
\begin{aligned}
\pi_{it} = \pi(\phi_{it}) &= \max_{x_{it}, T_{it} \in \{0,1\}} \{\pi(T_{it}, x_{it}; \phi_{it})\} \\
&= \max_{x_{it}, T_{it} \in \{0,1\}} \Bigg\{ \underbrace{\sum_{m \in \mathcal{N}} \left[\frac{1}{\sigma} \left(\mu \frac{\tau_{nmj} (1-s_{njt})^{T_{it}} c_{njt}}{\phi_{it} \eta^{T_{it}} f(\lambda_{njt-1}^T)} \right)^{1-\sigma} P_{mjt}^{\sigma-1} E_{mjt} \right]}_{:=\pi^d(T_{it};\phi_{it}) = \sum_{m\in\mathcal{N}} \pi^m(T_{it};\phi_{it})} \\
&\quad + x_{it} \Bigg[\underbrace{\frac{1}{\sigma} \left(\mu \frac{\tau_{nj}^x (1-s_{njt})^{T_{it}} c_{njt}}{\phi_{it} \eta^{T_{it}} f(\lambda_{njt-1}^T)} \right)^{1-\sigma} D_{jt}^f}_{:=\pi^x(T_{it};\phi_{it})} - c_{njt} F_j^x \Bigg] - T_{it} c_{njt} F_j^T \Bigg\},
\end{aligned} \tag{1.10}
$$

where x_{it} and T_{it} are binary export and adoption decisions, E_{mjt} are region m's total expenditures on sector j goods, and D_{jt}^f are exogenous foreign demands. $\pi^m(T_{it}; \phi_{it})$ are operating profits conditional on adoption status obtained from region m, and

[36] The assumption that the government finances its adoption subsidies through a labor tax is based on the labor market policies and the pro-business attitude of the authoritarian South Korean government in the 1970s. The government restricted firms' nominal wage growth to below 80% of the sum of inflation and aggregate productivity growth and enacted temporary provisions in 1971 to prohibit labor union activities (Kim and Topel, 1995). Also, see footnote 3 of Itskhoki and Moll (2019).

$\pi^d(T_{it};\phi_{it}) = \sum_{m\in\mathcal{N}} \pi^m(T_{it};\phi_{it})$ are the sum of all these profits from domestic regions. $\pi^x(T_{it};\phi_{it})$ are operating profits in foreign markets conditional on adoption status.

Adoption and Export Cutoff Productivities. Firms adopt technology and export their goods when the gains from these activities are larger than their fixed costs. Because these gains from adoption and exporting are higher when firms are more productive, firms' adoption and export decisions are characterized by cutoff productivities. Only firms with productivity above these cutoffs participate in adoption and exporting. We assume that fixed adoption costs are higher enough than fixed export costs that adopters always export to foreign markets.

The export cutoff $\bar{\phi}^x_{njt}$ is determined at where operating profits in foreign markets are equal to fixed export costs:

$$\bar{\phi}^x_{njt} = \frac{\mu c_{njt}(\sigma c_{njt} F^x_j)^{\frac{1}{\sigma-1}}}{f(\lambda^T_{njt-1})\Big((\tau^x_{nj})^{1-\sigma} D^f_{jt}\Big)^{\frac{1}{\sigma-1}}}. \tag{1.11}$$

The adoption cutoff $\bar{\phi}^T_{njt}$ is determined at where profits when adopting technology and profits when not adopting are equalized:

$$\bar{\phi}^T_{njt} = \frac{\mu c_{njt}(\sigma c_{njt} F^T_j)^{\frac{1}{\sigma-1}}}{\left(\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1} - 1\right)^{\frac{1}{\sigma-1}} f(\lambda^T_{njt-1})\Big(\sum_{m\in\mathcal{N}} \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt} + (\tau^x_{nj})^{1-\sigma} D^f_{jt}\Big)^{\frac{1}{\sigma-1}}}. \tag{1.12}$$

Under the distributional assumption, a share of adopters is expressed as:

$$\lambda^T_{njt} = 1 - G_{njt}(\bar{\phi}^T_{njt}) = \begin{cases} 1 & \text{if} \quad \bar{\phi}^T_{njt} \leq \phi^{min}_{njt} \\ \frac{(\bar{\phi}^T_{njt}/\phi^{min}_{njt})^{-\theta} - \kappa^{-\theta}}{1-\kappa^{-\theta}} & \text{if} \quad \phi^{min}_{njt} < \bar{\phi}^T_{njt} \leq \kappa\phi^{min}_{njt} \\ 0 & \text{if} \quad \bar{\phi}^T_{njt} > \kappa\phi^{min}_{njt}, \end{cases} \tag{1.13}$$

and a mass of adopters is obtained as $M^T_{njt} = M_{nj} \times \lambda^T_{njt}$. Similarly, a share of exporters is $\lambda^x_{njt} = 1 - G_{njt}(\bar{\phi}^x_{njt})$ and a mass of exporters is expressed as $M^x_{njt} =$

$M_{nj} \times \lambda^{x}_{njt}$.

Dynamic Complementarity. Spillovers generate dynamic complementarity in firms' adoption decisions: a higher share of adopters in the previous period increases gains from adoption in the current period.[37] The dynamic complementarity operates in two ways. The first way drives from complementarity between market size and productivity increases from adoption (Verhoogen, 2008; Bustos, 2011; Lileeva and Trefler, 2010). Because stronger spillovers increase the productivity of one region relative to other regions, firms in the more productive region will have a larger market and larger gains from adoption due to scale effects. This complementarity further incentivizes firms in the more productive region to adopt technology in the current period, which in turn magnifies spillover in subsequent periods.

The second form of dynamic complementarity derives from reduced fixed adoption costs. Because adoption costs are in units of input bundles, local sectoral aggregate goods are used for fixed adoption costs. Overall increases in productivity due to the spillover lower the costs of local sectoral aggregate goods, which in turn lowers fixed adoption costs (Matsuyama, 1995; Buera et al., 2021). Lower fixed adoption costs induce more firms to adopt technology in the current period, which in turn strengthens the spillover in subsequent periods. The spillover in one region also lowers fixed adoption costs in other regions through trade linkages.

1.5.3 Households.

Households make decisions of migration and consumption. For tractability, we assume that households are myopic and maximize per-period utility. Households in region n supply labor inelastically and earn wage w_{nt}. Because of the fixed en-

[37] In Appendix Section A.4.6, we provide direct empirical evidence on the dynamic complementarity. We find that firms that are located closer to neighboring adopters are more likely to adopt technology from foreign firms.

try assumption, the net profits of firms are redistributed back to households. Each household owns w_{nt} shares of a fund that collects profits from all firms across regions and sectors and redistributes back to households each period (Chaney, 2008).

Households have Cobb-Douglas preferences over final consumption baskets:

$$u(\{C_{jt}\}_{j\in\mathcal{J}}) = \prod_{j=1}^{J} C_{njt}^{\alpha_j}, \qquad \sum_{j\in\mathcal{J}} \alpha_j = 1, \tag{1.14}$$

where C_{njt} is the consumption of local sector j aggregate goods in region n at period t and α_j is the final good consumption shares. Households are subject to their budget constraints in each period: $\sum\limits_{j\in\mathcal{J}} P_{njt}C_{njt} = (1-\tau_t^w+\bar{\pi}_t)w_{nt}$, where P_{njt} is the price index of local sector j goods and $(1-\tau_t^w+\bar{\pi}_t)w_{nt}$ is the total income of households, which is the sum of after-tax wages $(1-\tau_t^w)w_{nt}$ and income from dividends $\bar{\pi}_t^h w_{nt}$.[38] We denote the ideal price index for households in region n using $P_{nt} = \prod_{j=1}^{J} P_{njt}^{\alpha_j}$.

At the end of the period, households choose which region to work and live in the next period. After making migration decisions, households supply labor and earn wages. The utility of a household h that lived in region m and moved to region n in period t is

$$\mathcal{U}_{mnt}^h(\epsilon_{nt}^h) = V_{nt}u(\{C_{jt}\}_{j\in\mathcal{J}})d_{mn}\epsilon_{nt}^h = V_{nt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\epsilon_{nt}^h, \tag{1.15}$$

where V_{nt} is an exogenous amenity in region n, d_{mn} are the utility costs of moving from m to n, and ϵ_{nt}^h is an idiosyncratic preference shock that is independent across households, regions, and periods.

We assume that ϵ_{nt}^h follows a Fréchet distribution with the shape parameter ν: $\epsilon_t^h \sim F(\epsilon) = exp(\epsilon^{-\nu})$, where $\epsilon_t^h = \{\epsilon_{nt}^h\}_{n\in\mathcal{N}}$ (Eaton and Kortum, 2002). Then a share

[38] Under the given portfolio structure, dividend per share is proportional to w_{nt}. Specifically, $\bar{\pi}_t^h = \Big(\sum\limits_{n\in\mathcal{N}}\sum\limits_{j\in\mathcal{J}}\int_{\omega\in\Omega_{nj}}\pi(\omega)d\omega\Big)/\Big(\sum\limits_{n\in\mathcal{N}} w_{nt}L_{nt}\Big)$.

of households moving to region n from region m in period t is given by

$$\mu_{mnt} = \frac{\left(V_{nt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\right)^{\nu}}{\sum_{n'=1}^{N}\left(V_{n't}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{n't}}d_{mn'}\right)^{\nu}}. \tag{1.16}$$

The shape parameter ν is migration elasticity that governs the responsiveness of migration flows to real income changes of destination.[39] The population of region n in period t is the sum of all migrants to region n from all other regions in time $t-1$. Therefore, the spatial distribution of population evolves according to the following law of motion:

$$L_{nt} = \sum_{m\in\mathcal{N}}\mu_{mnt}L_{mt-1}. \tag{1.17}$$

Welfare. In each period, the expected utility of each household of region n, prior to realizing idiosyncratic taste shocks ϵ_{nt}^h, is equal to

$$U_{nt} = \mathbb{E}\left[\max_m\left\{\mathcal{U}_{mn,t}^h(\epsilon_{nt}^h)\right\}\right] = \left[\sum_{m\in\mathcal{N}}\left(V_{nt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\right)^{\nu}\right]^{\frac{1}{\nu}}. \tag{1.18}$$

We define aggregate welfare as the average of U_{nt} weighted by population:

$$U_t^{agg} = \sum_{n\in\mathcal{N}}\frac{L_{nt-1}}{\sum_{m\in\mathcal{N}}L_{mt-1}}U_{nt}. \tag{1.19}$$

Aggregate Variables. For notational convenience, we define the average productivity including subsidies for all firms as follows:

$$\bar{\phi}_{njt}^{avg} = f(\lambda_{njt-1}^T)\left[\int_{\phi_{njt}^{min}}^{\bar{\phi}_{njt}^T}\phi_{it}^{\sigma-1}dG_{njt}(\phi_{it}) + \int_{\bar{\phi}_{njt}^T}^{\kappa\phi_{njt}^{min}}\left(\frac{\eta}{1-s_{njt}}\phi_{it}\right)^{\sigma-1}dG_{njt}(\phi_{it})\right]^{\frac{1}{\sigma-1}}.$$

$\bar{\phi}_{njt}^{avg}$ captures the average cost advantage of sector j firms in region n. $\bar{\phi}_{njt}^{avg}$ decreases in $\bar{\phi}_{njt}^T$ (higher λ_{njt}^T), higher s_{njt}, or higher λ_{njt-1}^T. The expression for the average

[39] Higher ν implies less heterogeneity of preference shocks across households, which makes the utility of households more sensitive to amenity-adjusted real income. Therefore, with higher ν, migration flows will be more sensitive to real income.

productivity including subsidies for exporters ($\bar{\phi}^{avg,x}_{njt}$) can be defined similarly, but the lower bound is replaced with $\bar{\phi}^{x}_{njt}$ instead of ϕ^{min}_{njt} because of selection effects induced by fixed exporting costs.

Aggregate variables in this economy can be expressed as a function of $\bar{\phi}^{avg}_{njt}$ and $\bar{\phi}^{avg,x}_{njt}$. Because of the distributional assumptions, these aggregate variables allow for closed-form expressions. See Appendix Section A.3.1 for detailed closed-form expressions for aggregate variables and their derivations. The price index is expressed as

$$P^{1-\sigma}_{njt} = \sum_{m \in \mathcal{N}} \left[M_{mj} \left(\frac{\mu \tau_{mnj} c_{mjt}}{\bar{\phi}^{avg}_{mjt}} \right)^{1-\sigma} \right] + (\tau^{x}_{nj} c^{f}_{jt})^{1-\sigma}. \tag{1.20}$$

Region n's share of the total sector j expenditure on goods from domestic region m and from Foreign are expressed as:

$$\pi_{mnjt} = \left(\frac{\tau_{mnj} c_{mjt} / \bar{\phi}^{avg}_{mjt}}{P_{njt}} \right)^{1-\sigma} \quad \text{and} \quad \pi^{f}_{njt} = \left(\frac{\tau^{x}_{nj} c^{f}_{jt}}{P_{njt}} \right)^{1-\sigma}. \tag{1.21}$$

Regional gross output for domestic expenditures R^{d}_{njt} and the total value of exports R^{x}_{njt} are expressed as:

$$R^{d}_{njt} = M_{nj} \left(\frac{\mu c_{njt}}{\bar{\phi}^{avg}_{njt}} \right)^{1-\sigma} \sum_{m \in \mathcal{N}} \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt} \quad \text{and} \quad R^{x}_{njt} = M^{x}_{njt} \left(\frac{\mu \tau^{x}_{nj} c_{njt}}{\bar{\phi}^{avg,x}_{njt}} \right)^{1-\sigma} D^{f}_{jt}. \tag{1.22}$$

The total regional gross output R_{njt} is the sum of R^{d}_{njt} and R^{x}_{njt}.

1.5.4 Equilibrium

Timing. We denote the geographic fundamentals and subsidies across regions and sectors as

$$\mathbf{\Psi}_t = \{\phi^{min}_{njt}, V_{nt}, D^{f}_{jt}, c^{f}_{jt}\} \quad \text{and} \quad \mathbf{s}_t = \{s_{njt}\}.$$

The timing of this model is as follows. Given $\{\lambda^{T}_{njt-1}, L_{nt-1}\}$, $\mathbf{\Psi}_t$, and $\mathbf{s}_t$, households make static consumption and migration decisions and firms make static adoption and export decisions in t. These decisions, production, consumption, and wages are determined by the static equilibrium in t, in which households maximize their utility, firms maximize their profits, and market clearing conditions are satisfied. $\{\lambda_{njt}^T, L_{nt}\}$, which are the outcomes of the static equilibrium in t, become the state variables in $t+1$ and so on.

Static Equilibrium. Given $\{\lambda_{njt-1}^T\}$, $\{L_{nt-1}\}$, $\boldsymbol{\Psi}_t$, and $\mathbf{s}_t$, firms maximize profits (Equation (1.10)), households maximize utility (Equation (1.14)), and the following market clearing conditions are satisfied each period.

Labor market clearing implies that labor supply is equal to labor demand in each region:

$$w_{nt}L_{nt} = \left[\sum_{j\in\mathcal{J}} \gamma_j^L \left(\frac{\sigma-1}{\sigma}R_{njt} + M_{njt}^T c_{njt} F_j^T + M_{njt}^x c_{njt} F_j^x\right)\right], \tag{1.23}$$

where the right hand side is the sum of labor used for production, fixed export costs, and fixed adoption costs.

The government budget is balanced each period:

$$\tau_t^w \sum_{n\in\mathcal{N}} w_{nt}L_{nt} = \sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{J}^T}\left[\frac{\sigma-1}{\sigma}\frac{s_{njt}-1}{s_{njt}} M_{nj}\int_{\bar{\phi}_{njt}^T}^{\kappa\phi_{njt}^{min}} r(\phi_{it})dG_{njt}(\phi)\right], \tag{1.24}$$

where $r(\phi_{it})$ are firm i's revenues. The left hand side of this equation is total government tax revenue and the right hand side is total government spending.

Region n's total expenditure on sector j goods is the sum of the total expenditure on intermediate inputs and final consumption goods in sector j:

(1.25)

$$E_{njt} = \sum_{k\in\mathcal{J}} \gamma_k^j \left(\frac{\sigma-1}{\sigma}R_{nkt} + M_{nkt}^T c_{nkt} F_k^T + M_{nkt}^x c_{nkt} F_k^x\right) + \alpha_j(1-\tau_t^w+\bar{\pi}_t^h)w_{nt}L_{nt}.$$

Goods market clearing implies that region n's total sector j gross output is the sum of the value of total exports and the value of the total demand for region n's sector

j goods across the Home regions:

$$R_{njt} = R^x_{njt} + \sum_{m \in \mathcal{N}} \pi_{nmjt} E_{mjt}. \tag{1.26}$$

Labor and goods market clearing conditions imply that trade is balanced.

Dynamic Equilibrium. In this economy, $\{\lambda^T_{njt}, L_{nt}\}$ are dynamic state variables that follow the laws of motions in Equations (1.13) and (1.17), respectively. The law of motion of λ^T_{njt} is the key equation of this model. This equation establishes a relationship between λ^T_{njt-1} to λ^T_{njt} and introduces dynamics in this economy, although all decisions made by agents are static.

We define the dynamic equilibrium of this economy as follows:

Definition I.1. Given initial shares of adopters $\{\lambda^T_{njt_0}\}$ and the path of the geographic fundamentals $\mathbf{\Psi}_t$ and subsidies $\{s_{njt}\}$, a dynamic equilibrium is a path of wages $\{w_{nt}\}$, price indices $\{P_{njt}\}$, a set of functions $\{p_{inmjt}(\omega)$, $q_{inmjt}(\omega)$, $p^x_{injt}(\omega)$, $q^x_{injt}(\omega)$, $T_{it}(\omega)$, $x_{it}(\omega)\}$, labor tax $\{\tau^w_t\}$, population $\{L_{nt}\}$, and shares of adopters $\{\lambda^T_{njt}\}$ such that

- **(Static Equilibrium)** for each period t, (i) firms maximize profits (Equation (1.10)); (ii) households maximize utility by making consumption decisions (Equation (1.14)); (iii) labor markets clear (Equation (1.23)); (iv) goods markets clear (Equation (1.26)); (v) trade is balanced, and (vi) the government budget is balanced (Equation (1.24));
- **(Law of Motion of Dynamic State Variables)** (vii) $\{L_{nt}\}$ follows the law of motion in Equation (1.17); and (viii) $\{\lambda^T_{njt}\}_{j \in \mathcal{J}^T}$ follows the law of motion in Equation (1.13).

Equilibrium conditions (i)-(vi) determine the static equilibrium allocation in each period. Conditions (vii) and (viii) determine the laws of motion for the dynamic state variables.

1.5.5 Analytical Results: Multiple Steady States

In this subsection, we show that multiple steady states can arise in a simplified model. We consider a closed economy with one sector and one region where labor is the only factor of production. We drop subscripts n and j for notational convenience. We make the following simplifying assumptions:

Assumption I.2. *(i)* $|\mathcal{N}| = |\mathcal{J}| = 1$ *and* $\tau^x_{nj} \to \infty$ *(closed economy with one region and one sector); (ii)* $M = 1$ *(normalization); (iii)* $\kappa \to \infty$ *and* $\phi^{min}_t = 1$ *(unbounded Pareto); (iv)* F^T *is in units of final goods (dynamic complementarity); and (v)* $\sigma > 2$ *(uniqueness).*

Assumptions I.2(i)-(iii) are imposed for analytical tractability. Under these assumptions, firms' exogenous productivity follows an unbounded Pareto distribution with a normalized location parameter and firm mass is normalized to be one. Assumption I.2(iv) is a source of dynamic complementarity in firms' adoption decisions in this environment. With only one region and the CES demand structure, the complementarity between market size and gains from adoption does not operate in this environment, and the dynamic complementarity comes only from fixed adoption costs in units of final goods.[40] Assumption (v) is a sufficient condition to guarantee a unique static equilibrium each period.[41]

[40] With only one region, each firm's increase in productivity due to spillovers is exactly canceled out by competition due to other firms' increases in productivity under the CES demand structure. Therefore, the overall increase in productivity through spillovers does not change the relative market size of each firm, which nullifies the complementarity between market size and gains from adoption. However, because fixed adoption costs are in units of final goods, the spillover from the previous period lowers fixed adoption costs in the current period, which further incentivizes more firms to adopt technology in the current period and generates dynamic complementarity. At the other extreme, when fixed adoption costs are in units of labor, there is no dynamic complementarity, and the equilibrium share of adopters λ^{T*}_t is not affected by λ^T_{t-1}, because overall productivity increase induced by the spillover increases labor demand, which in turn increases wages and the total fixed adoption cost $w_t F^T$. This is formally stated in Appendix Section A.3.2. Although we assume that fixed adoption costs are only in units of final goods for simplicity, as long as parts of fixed adoption costs are in units of final goods, the model generates dynamic complementarity.

[41] When a fixed adoption cost is in units of final goods, and $\sigma \leq 2$ holds, multiple static equilibria can arise each

By combining Equations (1.12) and (1.13), we can derive the analytical expression of the short-run equilibrium share of adopters $\lambda_t^{T*} = \lambda_t^{T*}(\lambda_{t-1}^T; \eta, \delta)$ conditional on a share of adopters in the previous period λ_{t-1}^T. The equilibrium share of adopters is determined at $\lambda_t^{T*}(\lambda_{t-1}^T; \eta, \delta) = \min\{\hat{\lambda}_t^T(\lambda_{t-1}^T; \eta, \delta), 1\}$, where $\hat{\lambda}_t^T(\lambda_{t-1}^T; \eta, \delta)$ is implicitly defined by the following equation[42]:

$$(1.27) \quad \hat{\lambda}_t^T(\lambda_{t-1}^T; \eta, \delta) = \Bigg[\underbrace{A(\hat{\lambda}_t^T(\lambda_{t-1}^T; \eta, \delta))^{2-\sigma}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda_{t-1}^T)}_{\text{Marginal adopters' net gains from adoption}}\Bigg]^{\frac{\theta}{\sigma-1}},$$

$$\text{where} \quad A(\lambda^T) = \left[\frac{\theta}{\tilde{\bar{\theta}}}\Big((\eta^{\sigma-1}-1)(\lambda^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} \quad \text{and} \quad f(\lambda^T) = exp(\delta\lambda^T).$$

The equilibrium share is characterized by the cutoff productivity level which is determined by the point at which the net gains from adoption for marginal adopters are equal to zero. Similarly, the time-invariant steady state share of adopters satisfies $\lambda^{T*} = \lambda_t^{T*} = \lambda_{t-1}^{T*}$ and is determined by $\lambda^{T*} = \lambda^{T*}(\lambda^{T*}; \eta, \delta)$.

Given any initial shares of adopters $\lambda_{t_0}^T$, this economy has a unique deterministic equilibrium path to the steady state due to Assumption I.2(v). Because static equilibrium is unique each period, there exists a unique sequence of static equilibrium that forms a unique deterministic dynamic path. λ_t^{T*} increases in λ_{t-1}^T due to dynamic complementarity. λ_t^{T*} also increases in two parameters: η and δ. η increases λ_t^{T*} by increasing the net gains for marginal adopters.[43] δ increases λ_t^{T*} by magnify-

period regardless of the existence of the spillover. This is because firms do not take the aggregate price index into account when making adoption decisions. When the share of adopters becomes larger, the aggregate price index becomes lower and this, in turn, decreases fixed adoption costs and vice versa. This degree of responsiveness of the price index to the share of adopters decreases in the values of the elasticity of substitution σ. When σ is sufficiently low, two static equilibria can arise where one has a higher share of adopters and the other has a lower share. By imposing $\sigma > 2$, we are ruling out the possibility of these multiple static equilibria. Matsuyama (1995) and Buera et al. (2021) have studied these types of multiple equilibria. Our model differs from their models because our multiple long-run steady states are generated because of the local spillover. Also, it is natural to assume $\sigma > 2$ because commonly calibrated parameter values for σ are larger than 2 (Broda and Weinstein, 2006).

[42] λ_t^{T*} is bounded by 1. $\lambda_t^{T*}(\lambda_{t-1}^T; \eta, \delta) = 1$ when $A(\hat{\lambda}_t^T(\lambda_{t-1}^T; \eta, \delta))^{2-\sigma} f(\lambda_{t-1}^T)\frac{\eta^{\sigma-1}-1}{\sigma F^T} \geq 1$.

[43] Note that two terms are related to the direct productivity gains governed by η in Equation (1.27): $(\eta^{\sigma-1}-1)$ and $A(\lambda_t^T)^{2-\sigma}$. The term $(\eta^{\sigma-1}-1)$ captures marginal adopters' net gains from adoption, which is internalized by their adoption decisions. The term $A(\lambda_t^T)^{2-\sigma} = A(\lambda_t^T)^{1-\sigma} \times A(\lambda_t^T)$ captures two composite general equilibrium effects of direct productivity gains. These two general equilibrium effects work in the opposite directions in the net gains for marginal adopters. First, $A(\lambda_t^T)^{1-\sigma}$ captures competition effects, which decrease in λ_t^T. As more firms adopt technology (increases in λ_t^T), the productivity of competitors increases, which in turn intensifies competition across

ing dynamic complementarity. Most importantly, we show that multiple steady can arise due to the dynamic complementarity in this economy. When multiple steady states exist, these steady states can be Pareto-ranked based on the steady state share of adopters, and the initial share of adopters $\lambda^T_{t_0}$ determines which steady state is realized in the long-run. These results are summarized in Proposition I.3.

Proposition I.3. *Under Assumption I.2,*

(i) (Uniqueness) Given any initial shares of adopters $\lambda^T_{t_0}$, there exists a unique dynamic equilibrium;

(ii) (Dynamic Complementarity) $\frac{\partial \hat{\lambda}^T_t(\lambda^T_{t-1};\eta,\delta)}{\partial \lambda^T_{t-1}} > 0$*;*

(iii) (Comparative Statistics) $\frac{\partial \hat{\lambda}^T_t(\lambda^T_{t-1};\eta,\delta)}{\partial \eta} > 0$ *and* $\frac{\partial \hat{\lambda}^T_t(\lambda^T_{t-1};\eta,\delta)}{\partial \delta} > 0$*;*

(iv) (Multiple Steady States) There exist intervals $[\underline{\delta}, \bar{\delta}]$ and $[\underline{\eta}, \bar{\eta}]$ such that holding other parameters constant, multiple steady states arise only for $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$;

and (v) (Pareto-Ranked) If multiple steady states exist, these steady states can be Pareto-ranked based on the equilibrium share of adopters.

The case of multiple steady states is illustrated in Panel A of Figure 1.3, where there are three different steady states with two basins of attraction.[44] The red locus is defined by Equation (1.27), where each point on the locus is a short-run equilibrium given λ^T_{t-1}. Given λ^T_{t-1}, λ^{T*}_t is determined in period t; and then given λ^{T*}_t, λ^{T*}_{t+1} is determined in the next period $t+1$; and so on. Therefore, the equilibrium moves along the red locus as time passes. The steady state is determined at the point where

firms and decreases marginal adopters' net gains due to increased competition (or decreased market size). The second general equilibrium effect is that a higher share of adopters decreases the price of final goods and therefore fixed adoption costs (Assumption I.2(iv)). Assumption I.2(v) ensures that the first general equilibrium effect dominates this second general equilibrium effect.

[44] In this economy, there are at most three multiple steady states because of the functional form assumption imposed on the spillover: $f(\lambda^T_{t-1}) = exp(\delta\lambda^T_{t-1})$. The imposed spillover functional form makes λ^T_t strictly convex in λ^T_{t-1} so that the red locus in Figure 1.3 intersects with the 45-degree line two times at the most. With a functional form assumption that generates a larger degree of nonlinearity, it is possible to have greater or fewer multiple steady states than three.

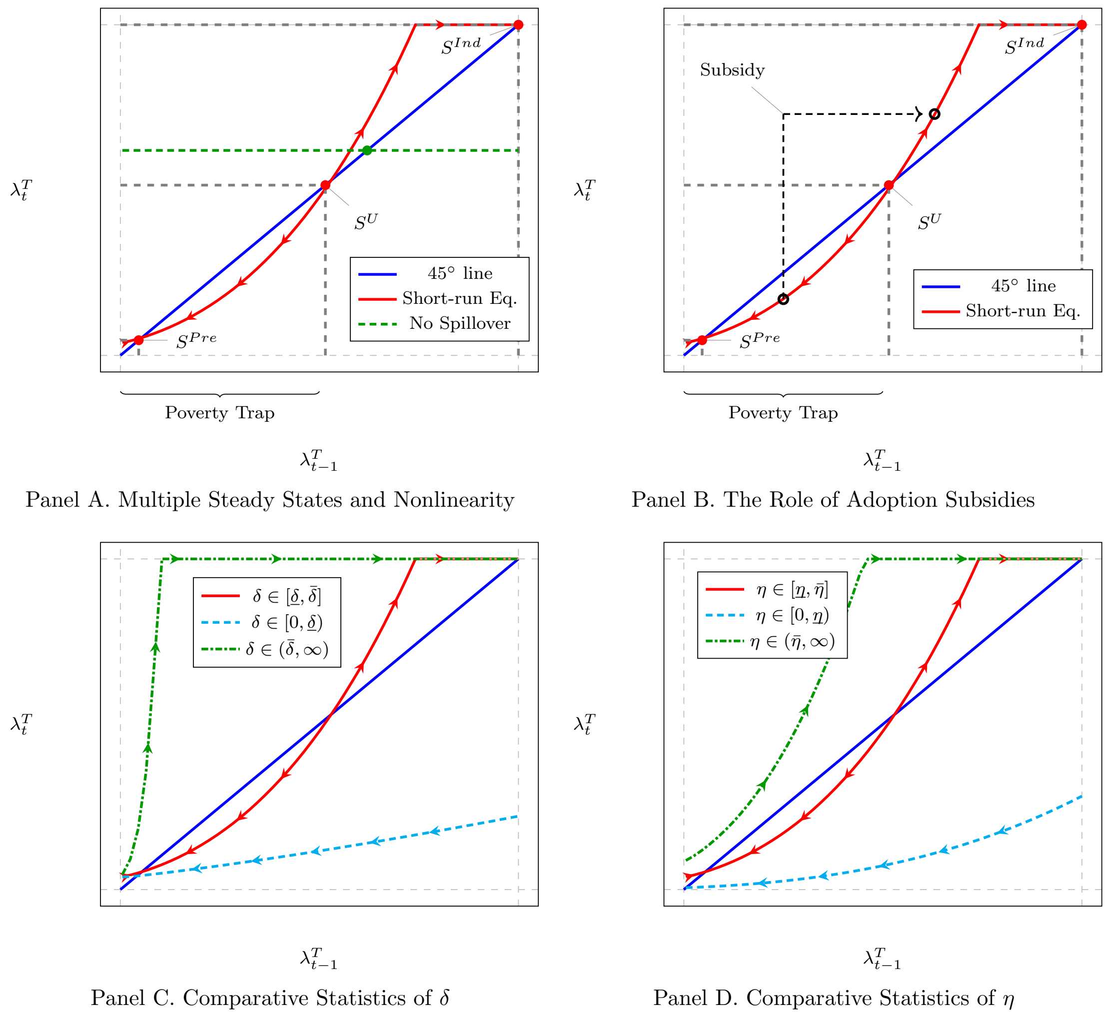


Figure 1.3: Multiple Steady States and Comparative Statistics

Notes. In Panel A, the multiple steady states arise only when the short-run equilibrium curve is sufficiently nonlinear. In Panel B, temporary subsidies can have permanent effects by moving an economy to a new transition path that converges to the higher-productivity steady state S^{Ind}. In Panels C and D, the multiple steady states arise only for the medium range of values of η and δ.

$\lambda^{T*}_{t-1} = \lambda^{T*}_t, \forall t$ holds; that is, where the red locus intersects with the 45-degree blue line. There are three intersection points: S^{Pre}, S^U, and S^{Ind}, which we label as the pre-industrialized, unstable, and industrialized steady states, respectively.

Because technology adoption increases firms' productivity, these steady states can be Pareto-ranked depending on the steady state share of adopters. At S^{Ind}, all firms adopt technology, and at S^{Pre} there is a smaller share of adopters than the other two, so S^{Ind} Pareto-dominates the other two steady states and S^{Pre} is Pareto-dominated by the other two.[45] S^U is unstable in that the economy converges to this steady state only when the initial condition is given by the value of S^U. The nonlinearity of the red locus means that it intersects with the 45-degree line multiple times and generates the multiple steady states, where the spillover ($\delta > 0$) generates such nonlinearity. For example, if there is no spillover ($\delta = 0$), there is always a unique steady state illustrated by the intersection of the green dashed horizontal line and the 45-degree line. When there is no spillover, the equilibrium share of adopters is determined regardless of the share of adopters in the previous period, which gives the horizontal line in the graph.

For the initial conditions given by $\lambda^T_{njt_0} \geq S^U$, the economy converges to S^{Pre}, and for $\lambda^T_{njt_0} \geq S^U$, the economy converges to S^{Ind}. Because firms do not internalize the spillover, if an economy is locked into the region $\lambda^T_{njt_0} \geq S^U$, it converges to S^{Pre}, although an economy has the potential to reach S^{Ind}. This region is known as a poverty trap in the literature (Azariadis and Stachurski, 2005).

Multiple Steady States and the Permanent Effects of Temporary Subsidies. When multiple steady states exist, temporary subsidies for technology adoption in the initial

[45] The fact that all firms adopt technology at S^{Ind} is the artifact of the fact that λ^T_t is strictly convex in λ^T_{t-1}, which comes from the imposed functional form assumption of the spillover.

period can have permanent effects that move an economy that is initially in the poverty trap to a new transition path that converges to an industrialized steady state. This is illustrated in Panel A of Figure 1.3. Suppose the initial condition is given as $\lambda^{T}_{njt_0} < S^{U}$, so that an economy converges to S^{Pre}. However, if the government implements a one-time policy that subsidizes technology adoption, this can shift the share of adopters above the S^{U} level, which causes an economy to converge to the industrialized steady state S^{Ind}. This can rationalize South Korea's pattern of industrialization toward heavy manufacturing sectors and the temporary policy between 1973 and 1979.

In this model, only multiple steady states can rationalize the permanent effects of temporary subsidies.[46] When there is only one steady state, subsidies temporarily shift the short-run equilibrium curve while they are provided, but the curve moves back to the original position after subsidies end and the economy converges to its original steady state.

Comparative Statistics. Proposition I.3(iv) implies that multiple steady states arise only for the medium ranges of $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$; that is when spillovers or direct productivity gains are neither too strong nor too weak. If these values are too high or too low, the dynamic complementarity becomes too strong or too weak and cannot generate enough nonlinearity of the short-run equilibrium locus, which means that it intersects with the 45-degree line only once. This is graphically illustrated in Panels C and D of Figure 1.3.

The comparative statistics offer one potential explanation for why the South Ko-

[46] Even if a unique steady state exists, there is room for policy interventions because of externalities. However, when a unique steady state exists, these policy interventions should be implemented in every single period in order to produce permanent effects. This point is graphically illustrated in Appendix Figure A.7. Kline and Moretti (2014), who studied the Tennessee Valley Authority program in the United States, did not detect nonlinearities in the agglomeration elasticity, so they concluded that the program did not have permanent effects because the agglomeration elasticity was not nonlinear enough to generate multiple steady states.

rean economy experienced remarkable transformation toward heavy manufacturing sectors when other developing countries did not. Both η and δ can be country-specific and depend on specific features of each country. η is generally related to the absorptive capacity of new technology and δ is related to degree of barriers to knowledge diffusion. For instance, countries with lower amounts of skilled labor endowments and higher language barriers may have lower values of η and δ. Compared to other developing countries, South Korea had higher amounts of skilled labor and used the same language (Rodrik, 1995), which can make South Korea have higher values of η and δ. South Korea could have been a special case because its values of η and δ were in a range that generated multiple steady states.

1.6 Taking the Model to the Data

In our quantitative exercises, we aggregate sectors into four categories: commodity, light manufacturing, heavy manufacturing, and service sectors. Given that most of the adoption occurred in the heavy manufacturing sectors, we assume that technology adoption is available only for the heavy manufacturing sector. The service sector is nontradable across regions and countries. We also aggregate the data to 42 regions.[47] One period in the model corresponds to 4 years in the data, so the timing of the spillover in the model is consistent with the spillover estimates in Section 1.4.2.

The model is fully parametrized by subsidies $\mathbf{s}_t$, geographic fundamentals $\mathbf{\Psi}_t$, and the following structural parameters

$$\mathbf{\Theta} = \{ \underbrace{M_{nj}}_{\substack{\text{Fixed}\\ \text{firm mass}}}, \underbrace{\theta, \kappa}_{\substack{\text{Pareto}\\ \text{distribution}}}, \underbrace{\eta, \delta, F_j^T}_{\substack{\text{Technology}\\ \text{adoption}}}, \underbrace{\sigma, \gamma_j^k, \gamma_j^L}_{\text{Production}}, \underbrace{\tau_{nmj}, F_j^x, \tau_{nj}^x}_{\text{Trade costs}}, \underbrace{\nu, d_{nm}}_{\substack{\text{Spatial}\\ \text{mobility}}}, \underbrace{\alpha_j}_{\text{Preferences}} \}.$$

We divide the set of structural parameters Θ into two subgroups depending on

[47] We aggregate up to 42 regions so that each region has at least two firms in each sector based on the administrative divisions in the 1970s and on electoral districts.

whether they are externally or internally calibrated:

$$\boldsymbol{\Theta}^E = \underbrace{\{\underbrace{\eta, \delta,}_{\substack{\text{Reduced-form}\\ \text{estimates}}} \quad \underbrace{M_{nj}, \theta, \sigma, \gamma_j^L, \gamma_j^k, \nu, d_{nm}, \tau_{nmj}, \tau_{nj}^x, \alpha_j\}}_{\text{Standard in the literature}}}_{\text{Externally calibrated parameters}} \quad \text{and} \quad \boldsymbol{\Theta}^M = \underbrace{\{\kappa, F_j^x, F_j^T\}}_{\substack{\text{Internally}\\ \text{calibrated}\\ \text{parameters}}}.$$

Our calibration procedure proceeds in two steps. First, we externally calibrate $\boldsymbol{\Theta}^E$, of which η and δ can be mapped to the reduced-form estimates in Section 1.4 and the remaining parameters are standard in the literature. Second, we internally calibrate $\boldsymbol{\Theta}^M$, subsidy $\mathbf{s}_t$, and geographic fundamentals $\boldsymbol{\Psi}_t$ using the method of moments.

1.6.1 Externally Calibrated Parameters

Technology Adoption $\{\boldsymbol{\eta}, \boldsymbol{\delta}\}$. η and δ are parameters that govern the magnitude of direct productivity gains and spillovers. The reduced-form estimates of direct productivity gains and spillovers in Section 1.4 can be mapped to η and δ of the model. Taking the log of adopters' sales, we can derive the following regression model:

$$\begin{aligned}\log Sales_{it} &= (\sigma - 1)\log(\eta) T_{it} \\ &\quad + \underbrace{\delta \lambda_{njt}^T + \log\Big(\sum_{m \in \mathcal{N}} \tau_{nmj} P_{mjt}^{\sigma-1} E_{mjt} + \tau_{nj}^x D_{jt}^f\Big)}_{\text{Absorbed out by exactly matching on region and sector}} + (\sigma - 1)\log\phi_{it},\end{aligned}$$

which can be mapped to our winners vs. losers specification (Equation (1.1)). By exactly matching on region and sector, we absorb out the spillover, the unit cost of production, and the market size that are common across firms within regions and sectors.[48] Exogenous cancellations by foreign firms can be interpreted as a shock to the fixed adoption cost F_j^T in our model framework that is orthogonal to firms' productivity $\log\phi_{it}$. We calibrate η using the point estimate of β_4^{diff} in Equation

[48]More precisely, we allow for variation in the spillover in our reduced-form regression model. In contrast, our model assumes that the spillover is common across firms within each region and sector. We can consistently estimate $(\sigma - 1)\log(\eta)$ when the cancellations are exogenous to both $\ln\phi_{it}$ and the residual of the spillover measure net of pair-common effects ($\text{Spill}_{inj(t-h)} - D_{pt}^{\tau}$).

(1.1). β_4^{diff} is consistent with one period of the model. Based on column (1) of Table 1.1, we set $\eta = exp(0.50)/(\sigma-1)$.

Similarly, taking the log on non-adopters' sales, we can derive the following regression model:

$$\log Sales_{it} = (\sigma-1)\delta\lambda_{njt}^{T} + \log\Big(\sum_{m\in\mathcal{N}} \tau_{nmj} P_{mjt}^{\sigma-1} E_{mjt} + \tau_{nj}^{x} D_j^f\Big) + (\sigma-1)\log\phi_{it}.$$

Although this is similar to our reduced-form specification for spillover (Equation (1.3)), they differ in terms of variation in spillovers within regions and sectors. λ_{njt}^{T} is common within regions and sectors in the model, whereas the spillover ($\text{Spill}_{inj(t-h)}$) in Equation (1.3) differs across firms within region-sector depending on their distances from adopters. To connect the model to the data, we rely on the fact that the reduced-form estimates of spillovers can be interpreted as the semi-elasticity of the local share of adopters when distances between firms are equal. We rely on this interpretation and assume that firms in the model are equally distant from each other in a finite set of regions. We set δ to be $4.5/(\sigma-1)$, which is the average value of estimates of spillovers in columns (1)-(5) of Table 1.2.

Spatial Mobility $\{\nu, d_{mn}\}$. We parametrize migration costs as a function of geographic distance: $d_{nm} = (dist_{nm})^{\zeta} \times \epsilon_{nm}^{d}$, where $dist_{nm}$ is the distance between regions n and m and ϵ_{nm}^{d} is a residual that is not explained by distance. We set ν to be 2, which is the estimate from Peters (2021). Using Equation (1.16), we derive a gravity equation for migration flows. ζ is externally calibrated by estimating this gravity equation. Using migration flows from 1990 to 1995, we run the following regression model:

$$\log \mu_{nm1990}^{1995} = -\nu\zeta \log dist_{nm} + \delta_m + \delta_n + \epsilon_{mn}^{d}, \tag{1.28}$$

where μ^{1995}_{nm1990} represent shares of migrants from region n to region m and δ_n and δ_m are region fixed effects.[49] To address attenuation bias arising from statistical zeros in the gravity models, we estimate the equation using the Poisson pseudo-maximum likelihood (PPML) (Silva and Tenreyro, 2006). Under the assumed value for ν, we obtain the value for ζ from the estimated coefficients. The gravity estimate implies that $\hat{\zeta} = 1.39/\nu$.[50]

Variable Trade Costs $\{\tau_{nmj}, \tau^x_{nj}\}$. We parametrize variable internal trade costs as a function of the geographic distance $\tau_{nmj} = (dist_{nm})^{\xi}$ and assume that ξ is the same across different sectors. We do not observe internal trade flows, so we borrow the estimates from the literature. We use the distance elasticity estimate from Monte et al. (2018) and set $\xi = 1.29/(\sigma - 1)$.

For international trade costs, we assume that firms have to ship their products to the nearest port and then pay both variable and fixed international trade costs at the port when they export or import. Under this assumption, international trade costs can be parametrized as $\tau^x = \tilde{\tau}^x \times (dist^{port}_n)^{\xi}$. $\tilde{\tau}^x$ represent variable costs incurred at the port. We set $\tilde{\tau}^x$ to be 1.7 following Anderson and Van Wincoop (2004). $(dist^{port}_n)^{\xi}$ represent variable costs associated with shipping from region n to the nearest port, where $dist^{port}_n$ is the distance between region n and the port and ξ is the same parameter of the parametrization of internal trade costs.[51]

[49] The estimation procedure is described in detail in Appendix Section A.5.5. The data on migration shares comes from the 1995 Population and Housing Census, which was the closest to our sample periods among the accessible population census data. Because of data availability, regions are aggregated up to 35 regions. μ^{1995}_{nm1990} is obtained as the total number of migrants who moved from region n to region m in the period 1990 to 1995 divided by the total population of region n in 1990. When we compute the total number of population and migrants, we restrict our sample age to 20 to 55.

[50] We find statistically significant results at 1% when we two-way cluster errors at origin and destination levels. The OLS estimates of Equation (1.28) is 1.30, which is similar to 1.39 obtained from the PPML. See Appendix Table A.19 for the detailed gravity estimates of migration flows. These estimated values are consistent with the estimates by recent papers. For example, Pellegrina and Sotelo (2021) find the estimated elasticity of Brazilian migration flows to distance is -1.32.

[51] When computing the nearest distance to ports, we use seven main ports in South Korea: Busan, Incheon, Gunsan, Guje, Pohang, Ulsan, and Yeosu.

The Remaining Parameters $\{\sigma, \theta, M_{nj}, \alpha_j, \gamma_j^L, \gamma_j^k\}$. The remaining parameters are the elasticity of substitution, Pareto shape parameter, exogenous firm mass, and Cobb-Douglas shares of preference and production function. Following Broda and Weinstein (2006), we set the elasticity of substitution σ to be 4. We set the Pareto shape parameter θ to be $1.06 \times (\sigma - 1)$ (Axtell, 2001).[52] We set M_{nj} to be proportional to the GDP share of each region and sector and set $\sum_{n \in \mathcal{N}} M_{nj} = 1$ following Chaney (2008). The Cobb-Douglas shares of preference (α_j) and production function (γ_j^k and γ_j^L) are taken from the input-output table for 1972.

1.6.2 Internally Calibrated Parameters

$\mathbf{\Theta}^M = \{F_j^x, F_j^T, \kappa\}$, $\mathbf{s}_t = \{s_{njt}\}$, and $\mathbf{\Psi}_t = \{\phi_{njt}^{min}, V_{nt}, D_{jt}^f, c_{jt}^f\}$ are calibrated using the method of moments. Our calibration procedure requires moments from firm-level data and a set of cross-sectional aggregate variables in 1972, 1976, and 1980 which cover the periods when the subsidies were provided between 1973 and 1979. The required set of aggregate variables include region-sector level gross output $\{R_{njt}\}$, regional population distribution $\{L_{nt}\}$, aggregate export and import shares, initial shares of adopters $\{\lambda_{nj-1}^T\}$ and initial population distribution $\{L_{n,-1}\}$. $\{\lambda_{nj-1}^T\}$ and $\{L_{n,-1}\}$ are taken as given when solving the model for $t = 1$. Appendix Section A.5.2 explains the algorithm of the calibration procedure and how we construct the data inputs in detail.

[52] Under the Pareto distributional assumption with shape parameter θ, the distribution of firm sales follows the Pareto distribution with shape parameter $\theta/(\sigma - 1)$. Many previous studies that have estimated θ using firm sales distribution have found that $\theta/(\sigma - 1)$ is close to 1 (Axtell, 2001; di Giovanni et al., 2011; di Giovanni and Levchenko, 2012, 2013).

Constrained Minimization Problem. We calibrate $\boldsymbol{\Theta}^M$, $\boldsymbol{\Psi}_t$, and $\mathbf{s}_t$ by solving the following constrained minimization problem:

(1.29)

$$\{\hat{\boldsymbol{\Theta}}^M, \hat{\mathbf{s}}_t\} \equiv \underset{\boldsymbol{\Theta}^M, \mathbf{s}_t}{\arg\min}\{L(\boldsymbol{\Theta}^M, \mathbf{s}_t)\} = \underbrace{(\bar{m} - m(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t))'\mathbf{W}(\bar{m} - m(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t))}_{\text{Micro moments}}$$

$$\text{subject to} \quad \underbrace{\mathbf{C}(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t) = \mathbf{C}_t}_{\text{Aggregate data}}, \quad t \in \{1, 2, 3\}.$$

$\mathbf{W}$ is a weighting matrix. $\bar{m}$ and $m(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t)$ are the model moments and data counterparts of the objective function. $\mathbf{C}(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t) = \mathbf{C}_t$ are the imposed constraints. $\mathbf{C}(\boldsymbol{\Theta}^M, \mathbf{s}_t, \boldsymbol{\Psi}_t)$ and $\mathbf{C}_t$ are the model moments and data counterparts of the constraints. For the weighting matrix, we use the identity matrix.

Identification of Subsidies. We do not observe subsidies directly in the data. Following the historical narrative, subsidies are provided only in $t = 2, 3$ in the model, which corresponds to 1976 and 1980 in the data. Given the lack of information on the distribution of subsidies across regions, we assume that the government provided the same subsidy level $\bar{s}$ across regions in $t = 2, 3$:

$$s_{njt} = \begin{cases} \bar{s} & \text{if} \quad t \in \{2, 3\}, \quad \forall n \in \mathcal{N}, \quad \forall j \in \mathcal{J}^T \cap \mathcal{J}^{policy} \\ 0 & \text{otherwise}, \end{cases} \tag{1.30}$$

where $\mathcal{J}^{policy}$ is a subset of sectors that the government targeted.

Despite the lack of data on subsidies, with the above parametrization of subsidies, we can identify $\bar{s}$ using the model structure and the reduced-form estimates that measure direct and spillover benefits from adoption. Our intuition is that given information about the benefits from adoption (direct productivity gains and spillovers), the increases in shares of adopters in 1976 or 1980 relative to 1972 are attributable to the policy. The following proposition summarizes this result.

Proposition I.4. *(Identifying Moment for Subsidies) Suppose a subsidy plan is given by Equation* (1.30)*. Assume that (a) exogenous firm productivity follows the unbounded Pareto distribution ($\kappa \to \infty$), (b) goods are freely tradable ($\tau_{nmj} = 1$ and $\tau^x_{nj} = 1$), and (c) $j \in \mathcal{J}^T$ are symmetric. Consider the following regression model for $j \in \mathcal{J}^T$, $n \in \mathcal{N}$:*

$$\ln \lambda^T_{njt} - \theta\delta\lambda^T_{njt-1} = \beta^{policy} \times D^{policy}_{jt} + \delta_{nt} + \epsilon_{njt},$$

where D^{policy}_{jt} is a dummy variable of whether $j \in \mathcal{J}^{policy}$, and δ_{nt} are time-varying regional fixed effects. Then, when $\mathbb{E}[\ln \phi^{min}_{njt} | D^{policy}_{jt}] = 0$ holds,

$$\hat{\beta}^{policy} \xrightarrow{p} \beta^{policy} = \frac{\theta}{\sigma - 1}\left[\ln\left(\left(\frac{\eta}{1-\bar{s}}\right)^{\sigma-1} - 1\right) - \ln(\eta^{\sigma-1} - 1)\right],$$

and $\hat{\beta}^{policy}$ uniquely identifies $\bar{s}$ for given values of η, δ, σ, and θ.

The proposition shows that sudden increases in shares of adopters in 1980 captured by β^{policy} are informative about subsidies when they are uncorrelated with exogenous natural advantages; that is, when $\mathbb{E}[\ln \phi^{min}_{njt} | D^{policy}_{jt}] = 0$ holds. This proposition motivates our approach. Since the simplifying assumptions of Proposition I.4 do not hold exactly in either the model or the data, we identify the subsidy level by indirect inference. In particular, using both actual and model-generated data, we estimate the following regression for only the heavy manufacturing sector in 1972 and 1980 using the PPML to incorporate zeros:

$$\ln \lambda^T_{n,heavy,t} = \alpha + \beta^{policy} \times D^{policy}_t + \beta_1 \lambda^T_{n,heavy,t-1} + \epsilon_{n,heavy,t}. \tag{1.31}$$

Then, we use the estimated β^{policy} from the actual data as the identifying moment for $\bar{s}$ and fit the estimated β^{policy} from the model-generated data to this moment (Nakamura and Steinsson, 2018).

Equation (1.31) differs from the regression model in Proposition I.4 in two ways. First, because the heavy manufacturing sector is the only sector where technology adoption is available in our quantitative exercises, we cannot control for δ_{nt}, and D_t^{policy} cannot be separately identified from time fixed effects.[53] However, we show that $\hat{\beta}^{policy}$ is still informative for $\bar{s}$ in Appendix Section A.5.4. Second, we control for previous shares rather than subtract them from current shares in dependent variables.[54] The estimated coefficients for β^{policy} and β_1 are 0.65 and 5.62, and statistically significant at the 1% level.[55]

Objective Function: Micro Moments, $\{\boldsymbol{\Theta}^M, \bar{s}\}$. We identify $\boldsymbol{\Theta}^M = \{F_j^T, F_j^x, \kappa\}$ and subsidy rate $\bar{s}$ using micro moments. $\bar{s}$ is identified by the identifying moment discussed above. We identify fixed adoption costs F_j^T using the median of shares of adopters across regions in 1972 and 1980. We identify κ using the share of regions with zero adoption in 1972 and 1980. κ rationalizes zero adoption in some regions observed in the data. If κ is sufficiently low; that is, if the gap between the Pareto lower and upper bounds becomes narrower, the cutoff adoption productivity becomes larger than the Pareto upper bound $\kappa\phi_{njt}^{min}$ for some regions, resulting in zero adoption in these regions. We calibrate fixed export costs of the light and heavy manufacturing sectors F_j^x to match the median shares of exporters across regions in 1972.[56] Because we do not have detailed data on firms in the commodity sector, we

[53] More specifically, we run this regression for shares of adopters in the heavy manufacturing sector in 42 regions for 1972 and 1980, so we use 84 samples in total. Note that we assumed that (i) technology adoption is available only for heavy manufacturing firms and (ii) that common subsidies are provided across regions, and (iii) that we aggregate heavy manufacturing sectors into one sector when we took the model to the data, so we cannot control for region, sector, or time fixed effects. Ideally, a richer model that incorporates multiple heavy manufacturing sectors or more information on subsidy schedules across regions will allow us to control for additional fixed effects.

[54] This is because the PPML is not defined for dependent variables with negative values and subtracting the previous shares from the current shares with zero values generates observations with dependent variables that take negative values.

[55] The value of the estimated coefficient for β_1 (5.62) that corresponds to $\theta \times \delta$ in the model is consistent with the externally calibrated values $4.77 = 1.06 \times 4.5 = \theta \times \delta$. The estimation procedure and results are reported in Appendix Table A.18.

[56] Our firm balance sheet data has information on exports. However, many observations were missing. Given that export data are very noisy, we do not use export information for our reduced-form empirical analysis, but only for computing the moment on shares of exporters for our quantitative analysis.

Table 1.3: Calibration Strategy

Parameters			Identification / Moments
	Description	Value	
	External calibration		
	Structural parameters		
η	Direct productivity gains	1.3	Winners vs. Losers, Table 1.1 col. 1 $(\sigma - 1)\log(\eta) = 0.5$
δ	Spillover semi-elasticity	2.25	Spillover estimate, Table 1.2 $4.5 = (\sigma - 1)\delta$
σ	Elasticity of substitution	3	Broda and Weinstein (2006)
θ	Pareto shape parameter	2.12	Axtell (2001), $\theta/(\sigma - 1) = 1.06$
ν	Migration elasticity	2	Peters (2021)
ζ	Migration cost, $d_{mn} = (dist_{nm})^{\zeta}$	0.78	Gravity estimates
ξ	Internal trade cost, $\tau_{nmj} = (dist_{nm})^{\xi}$	0.43	Monte et al. (2018)
$\bar{\tau}^x$	International trade costs, $\tau^x_{nj} = \bar{\tau}^x(dist^{port}_{nm})^{\xi}$	1.7	Anderson and Van Wincoop (2004)
α_j	Preferences		IO table, 1972
γ^k_j	Production		IO table, 1972
M_{nj}	Exogenous firm mass		Value added, 1972 (Chaney, 2008)
	Internal calibration: Method of moment		
	Structural parameters		
F^T_j	Fixed adoption cost	0.28	Share of adopters, heavy mfg.
F^x_j	Fixed export cost, commodity & light mfg.	0.06	Share of exporters, light mfg.
F^x_j	Fixed export cost, heavy mfg.	0.05	Share of exporters, heavy mfg.
κ	Pareto upper bound	4.42	# of regions with zero adoption
	Geographical fundamentals		
ϕ^{min}_{nj}	Natural advantage (Pareto lower bound)		Dist. region & sector sales, 1972, 1976, 1980
D^f_j	Foreign market size		Sectoral export intensity, 1972, 1976, 1980
c^f_j	Foreign price of imported inputs		Sectoral import intensity, 1972, 1976, 1980
V_{nt}	Amenity		Pop. dist., 1972, 1976, 1980
	Subsidy		
$\bar{s}$	Subsidy rate	0.11	Identifying moment $\hat{\beta}^{policy}$, Equation (1.31)

Notes. This table reports calibrated objects of the model, their values, and their identifying moments. The calibration procedure is described in Appendix Section A.5.2.

set the fixed export costs of the commodity sector to be the same as those of the light manufacturing sector.

Constraints: Aggregate Data, $\boldsymbol{\Psi}_t$. The constraints in Equation (1.29) identify geographic fundamentals $\boldsymbol{\Psi}_t$. We impose the constraints such that shares of gross output at the region and sector levels, aggregate export and import shares, and regional population distribution of the model (Equations (1.16), (1.21), (1.22)) are exactly fitted to the counterpart of the data in 1972, 1976, and 1980. The number of constraints is the same with the dimension of the geographic fundamentals.[57] Therefore, for any given parameters $\boldsymbol{\Theta}^M$ and subsidy rate $\bar{s}$, the geographic fundamentals are exactly identified by these constraints and there exists a set of geographic fundamentals that rationalizes the data.

Because geographic fundamentals are exactly identified, we can identify the average productivity including subsidies $\bar{\phi}_{njt}^{avg}$ following the model-inversion logic from Allen and Arkolakis (2014).[58] However, we cannot identify what portion of $\bar{\phi}_{njt}^{avg}$ is attributable to natural advantages ϕ_{njt}^{min}, shares of adopters λ_{njt}^{T}, or subsidies $\bar{s}$ from aggregate data alone. To isolate ϕ_{njt}^{min}, λ_{njt}^{T}, and $\bar{s}$ from $\bar{\phi}_{njt}^{avg}$, we need information on fixed adoption costs F_j^T and subsidies $\bar{s}$ from the micro moments.

1.6.3 Calibration Results and Model Fit

Table 1.3 presents the summary of our calibration strategy and the values of the externally and internally calibrated parameters. The estimated adoption cost is 5.6 times larger than the estimated fixed export cost. The estimated subsidy rate is 0.11,

[57] The dimension of fundamentals is $|\{1972, 1976, 1980\}| \times (|\mathcal{N}| \times |\mathcal{J}| + 2 \times |\mathcal{J}^x| + |\mathcal{N}|)$, where $|\{1972, 1976, 1980\}|$ is the number of years when the model is exactly fitted to the region and sector data, $|\mathcal{N}| \times |\mathcal{J}|$ are the number of ϕ_{nj}^{min}, $|\mathcal{J}^x|$ is the number of D_j^f and c_j^f, and $|\mathcal{N}|$ is the number of V_n.

[58] By fitting the input-output tables, we can only identify relative productivity differences across regions and sectors, but we cannot identify aggregate shifters of productivity. Thus, when we fit gross output shares at regional and sectoral levels, we normalize ϕ_{njt}^{min} of one region and sector pair to 1 for each period. This is not a big concern because our interest is the comparison between the baseline economy and the counterfactual economy, which differences out the common aggregate components.

Table 1.4: Model Fit

Moment	Model	Data
Identifying moment $\hat{\beta}^{policy}$, Equation (1.31)	0.65	0.83
Med. shares of exporters in 1972, light mfg.	0.22	0.21
Med. shares of exporters in 1972, heavy mfg.	0.14	0.18
Med. shares of adopters in 1972	0.06	0.07
Med. shares of adopters in 1982	0.12	0.19
Share of zero adoption regions in 1972	0.59	0.53
Share of zero adoption regions in 1982	0.83	0.94

Notes. This table presents the values of the internally calibrated parameters and their identifying moments in the data.

which indicates that adopters are subsidized with 11% of input expenditures. Table 1.4 reports the model fit. The data moments are well-approximated in the model.

Non-targeted Moments. Our calibration strategy only fits the cross-sectional data for 1972, 1976, and 1980 and does not fit the evolution of variables after 1980. Also, we do not target employment directly. However, our model fits the evolution of heavy manufacturing's share of GDP quite well even after 1980 and the evolution of its share of employment between 1972 and 1980 (Panels A and B of Figure 1.4), which are non-targeted moments.

In Appendix Figure A.9, we compare regional shares of the heavy manufacturing sector's gross output computed from the data in 2004 and those calculated from the model of the corresponding model period.[59] Although we do not directly target the spatial distribution of the gross output of the heavy manufacturing sector, the spatial distribution computed from the model is qualitatively and quantitatively very similar to that observed in the data.

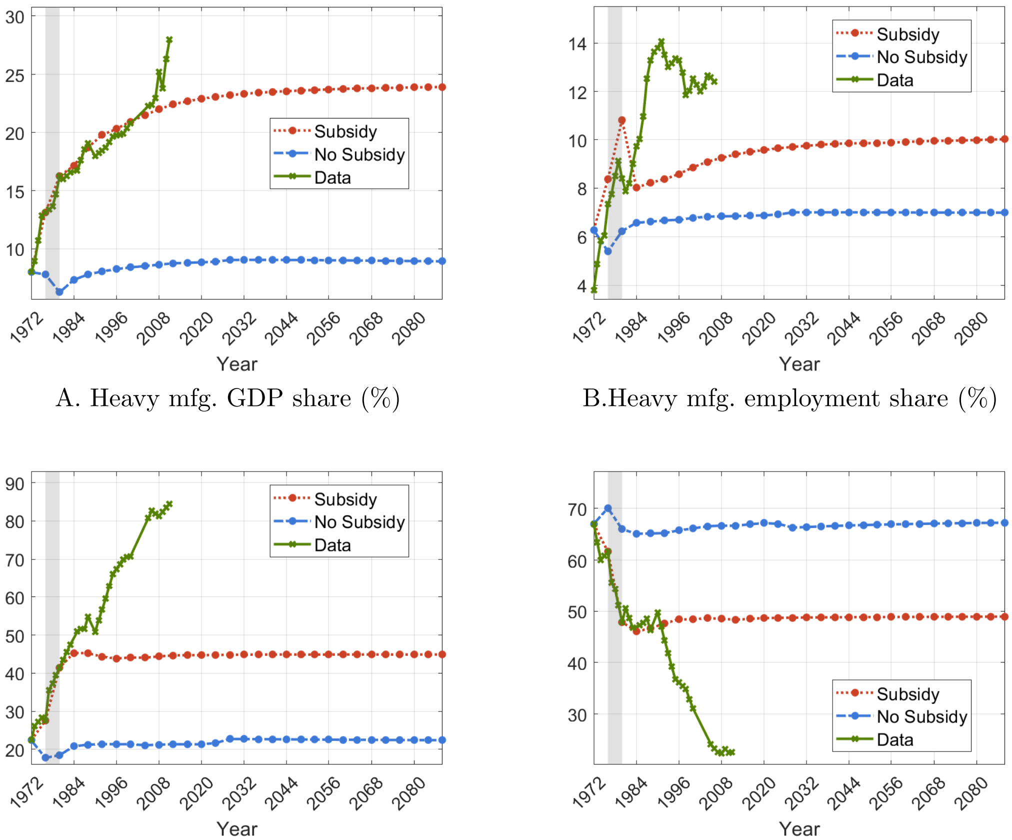
[59] We use the Mining and Manufacturing Survey that covers the universe of establishments with more than 5 employees.

1.7 The Aggregate and Regional Effects of the Temporary Adoption Subsidy

In this section, we ask how the aggregate and regional patterns of industrialization in South Korea would have evolved differently if the temporary subsidies had not been provided. In the baseline economy, the subsidies are provided, whereas the subsidies are not provided in the counterfactual economy. We compare these baseline and the counterfactual economies. Unlike the simplified model in Section 1.5.5 where there is a maximum of three steady states, the full quantitative model potentially admits a larger number of steady states. Which steady state will be reached in the long-run is of computational question, given calibrated values of $\{\mathbf{\Psi}_t, \bar{s}, \mathbf{\Theta}\}$ that are chosen to match cross-sectional data in 1972, 1976, and 1980 rather than chosen arbitrarily.

Figure 1.4 reports our main counterfactual results. In Panels A, B, C, and D, we compare the heavy manufacturing's shares of GDP, employment, and exports, and the light manufacturing's shares of exports. Had temporary adoption subsidies not been provided, South Korea's pattern of industrialization and its comparative advantage would have evolved differently. When compared to the steady state of the baseline economy, heavy manufacturing's share of GDP would have decreased by 15 percentage points, its share of employment would have decreased by 3 percentage points, and its share of exports would have decreased by 22.5 percentage points, and these changes would have been permanent in the steady state of the counterfactual economy. The reason why our model does not explain the evolution of the shares of employment and export after 1980 well is that we do not directly target evolution of the model after 1980.

Panel A of Figure 1.5 reports the average productivity of each region under the baseline and counterfactual economies. We define the average productivity as



A. Heavy mfg. GDP share (%)

B.Heavy mfg. employment share (%)

C. Heavy mfg. export share (%)

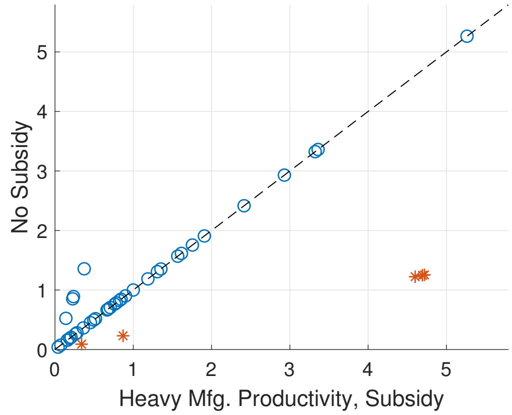
D. Light mfg. export share (%)

Figure 1.4: Results of the Counterfactual Analysis

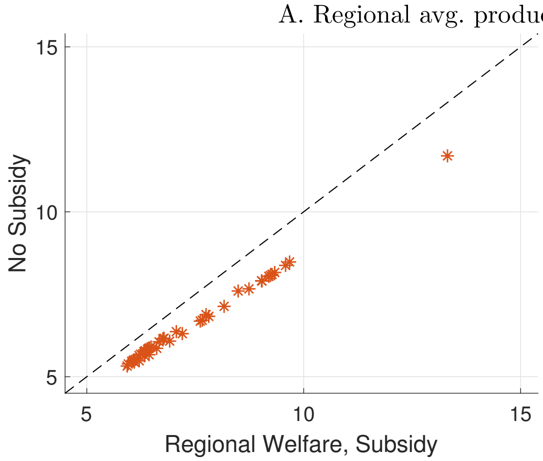
Notes. This figure plots the counterfactual results. The green solid line plots the actual data computed from the input-output tables. The red dotted line plots the outcomes of the baseline economy and the blue dotted line plots the outcomes of the counterfactual economy.

$M_{nj}[\int z_{it}(\phi)^{\sigma-1}dG_{njt}(\phi)]^{1/(\sigma-1)}$.[60] The x and y axes are the average productivity of the heavy manufacturing sector in each region under the baseline and counterfactual economies, respectively. Dots located below the 45 degree line, denoted as red stars, represent regions that have higher levels of productivity in the baseline when compared to the counterfactual. The figure shows that only five regions have higher productivity levels in the steady state of the baseline economy when compared to that of the counterfactual economy. Most of the regions have the same level of productivity in both steady states. This implies that the aggregate industrialization

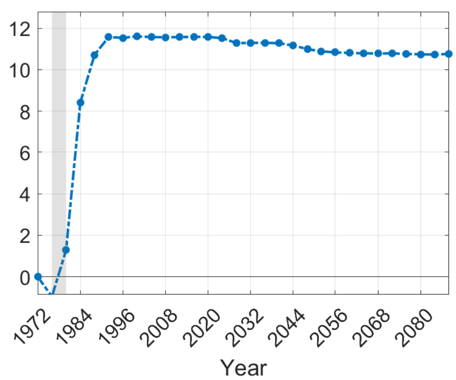
[60] Because M_{nj} and ϕ_{njt}^{min} are not separately identifiable under the fixed entry, $M_{nj}[\int z_{it}(\phi)^{\sigma-1}dG_{njt}(\phi)]^{1/(\sigma-1)}$ can be considered to be the average productivity when $M_{nj} = 1, \forall n, j$.



A. Regional avg. productivity in the steady state



B. Regional welfare in the steady state



C. Aggregate welfare gain (%)

Figure 1.5: Counterfactual Results. Welfare and egional Average Productivity

Notes. This figure plots the counterfactual results. Panel A reports the regional average productivity defined as $M_{nj}[\int z_{it}(\phi)^{\sigma-1}dG_{njt}(\phi)]^{1/(\sigma-1)}$. The x and y axes plot each region's average productivity under the baseline and counterfactual economies. Panel B reports regional welfare (Equation (1.18)). The x and y axes plot each region's welfare under the baseline and counterfactual economies. In Panels A and B, each dot is colored red if a corresponding region experienced increases in the average productivity and regional welfare. Panel C reports the ratio of the aggregate welfare (Equation (1.19)) of the baseline economy to that of the counterfactual economy.

toward the heavy manufacturing sector in the baseline economy is driven by large productivity increases of these five regions.

Panel B of Figure 1.5 plots the regional welfare gains in the steady states. The x and y axes are the regional welfare in the steady state under the baseline and counterfactual economies, respectively. In the steady states, all regions have higher welfare levels in the baseline than the counterfactual. Large productivity increases of a few regions and their specialization into the heavy manufacturing sector led to increases in welfare across all regions through trade linkages.

Panel C of Figure 1.5 plots the aggregate welfare gains in the baseline economy over the counterfactual economy. The aggregate welfare of the baseline is 10.7% permanently higher than the counterfactual once the economies reach steady states. The discounted utility ($\sum_{t=1}^{\infty} U_t^{agg}$) is also 10% higher in the baseline than the counterfactual. At the beginning of the implementation of the subsidies, the aggregate welfare of the baseline first decreases in the short run compared to the counterfactual because calibrated subsidies are not optimally designed.[61]

Roundabout Production. We find that a roundabout production structure plays an important role in generating permanent effects of subsidies. A roundabout production structure amplifies the impact of subsidies through cost and demand linkages (Krugman and Venables, 1995).[62] Because of these linkages, complementarity between firm-scale and gains from technology adoption causes more firms to adopt technology. We do the same counterfactual exercises with a new production structure where labor is the only factor of production, and there are no intermediate inputs. The results are reported in Appendix Figure A.11. Holding other parameters, subsidies, and geographic fundamentals constant, we find that both the baseline and the counterfactual economies converge to the same steady state.

Geography: Foreign Market Size and Migration Costs. We examine how geography interacts with the effects of temporary adoption subsidies. When we compare the baseline and counterfactual economies with and without the subsidies, we change geographical features of the South Korean economy to examine how its long-term effects differ from the main results in Figure 1.4. We specifically examine the role

[61] Analyzing the optimal subsidy in this economy is outside the purview of this paper. For the optimal policy, see Bartelme et al. (2020), Fajgelbaum and Gaubert (2020) and Lashkaripour and Lugovskyy (2020) in the static setting.

[62] Heavy manufacturing sectors had disproportionally larger own-cost shares of production γ_j^j than other sectors. Own-cost shares of production were 0.09 for commodities, 0.26 for light manufacturing, 0.46 for heavy manufacturing, and 0.13 for service.

of foreign market size and migration costs. We focus on foreign market size because of the large increase in the volume of South Korea's exports in the 1960s and 1970s and narratives that suggest that export expansion played an important role in South Korea's economic development.[63] We study migration costs because there were dramatic increases in migration flows from rural to urban areas in South Korea in the 1970s. This migration pattern is a common feature during industrialization.[64]

We examine how the effects of subsidies would have been if foreign market size had been lower. We decrease the foreign market size of the heavy manufacturing sector D_{jt}^{f} so that export shares in the heavy manufacturing sector in 1972 was 6.6%. This is the 1966 level; it replaced the 1972 level of 22%. The results are reported in Appendix Figure A.13. The gap between the heavy manufacturing GDP shares in the two steady states is about 5 percentage points, which is 10 percentage points smaller than the main results in Figure 1.4. These results provide suggestive evidence that exports and subsidies together might have played an important role in shaping South Korea's economic development.

We next examine how the effects of subsidies would have been if migration costs had been higher. We set migration costs to be 10% higher than the baseline calibrated value. Because of higher migration costs, fewer workers move toward regions with higher productivity brought about by technology adoption, which in turn increases wages and the cost of production. Because of the complementarity between firm

[63] Dramatic rapid increases in South Korea's exports were the outcomes of the government's export-promotion policy and increases in foreign demand shocks. South Korea joined the General Agreements on Tariff and Trade (GATT) in 1967 during the Kennedy Round and eliminated tariffs on imported inputs for exports (Connolly and Yi, 2015). It also devalued its over-valued currency in 1964, which boosted its exports (Irwin, 2021). Also, the United States' demand for foreign imports increased significantly in the period 1960 to 1980. During that period, shares of the United States' imports in the total gross national product rose from 6% to 22%.

[64] According to the World Development Indicators (World Bank), the rural population of South Korea decreased from 60 to 40% between 1970 and 1982. Migrants as a percent of the total population increased from 12.6% in 1970 to 21.9% in 1982. Many developing countries underwent rapid transitions from rural to urban during industrialization in the twentieth century. See Table 1 of Lucas (2004). Young (1995) also finds that labor reallocation into manufacturing played a significant role in manufacturing growth in the East Asian countries. Higher levels of migration costs may hinder labor reallocation into manufacturing.

scale and gains from adoption, fewer firms would adopt technology. These results are reported in Appendix Figure A.12. The difference between the heavy manufacturing sector's share of GDP for the two steady states is around 9 percentage points, which is 6 percentage points smaller than the main results in Figure 1.4.

Comparative Statistics. We conduct the comparative statistics of δ and η to examine how the parameters we choose drive these multiple steady states. In Appendix Figure A.10, we show that the differences between the outcomes of the baseline and counterfactual economies in the steady states become negligible when either δ or η is too low, consistent with the comparative static results of Proposition I.3(iv) in the simplified model.

1.8 Conclusion

We find that the impact of technology adoption on late industrialization in South Korea was significant both empirically and quantitatively. Our finding confirms a widely held belief by economists and policymakers that technology adoption can foster economic development of developing countries. We find that technology adoption not only directly benefited adopters but also had large local spillover effects. Based on these findings, we build a dynamic spatial model in order to conduct a counterfactual analysis of the South Korean government policy that provided temporary subsidies for technology adoption in the heavy manufacturing sectors. Using a quantitative model calibrated to firm-level data and to econometric estimates, we show that temporary adoption subsidies can have a permanently large impact on an economy by moving it to a new transition path that converges to a more industrialized steady state.

We believe that our empirical findings and quantitative results are important for two reasons. First, they highlight that externalities may explain why technologies diffuse slowly to developing countries and why appropriate policy interventions might be necessary to boost productivity. Second, we show that knowledge flows from developed countries to developing countries can be an important source of economic development.

Although we have mainly focused on the spatial spillover of technology adoption, there might be many other sources of externalities and frictions that hinder firms in developing countries from adopting more advanced technology. We abstracted from both uncertainties about future technology and forward-looking technology adoption decisions by firms. Incorporating more realistic assumptions on agents' beliefs in the model and how these beliefs interact with multiple equilibria would be an interesting extension. We leave these questions for future research.

CHAPTER II

The Long-Term Effects of Industrial Policy

2.1 Introduction

Many countries at different stages of development have engaged in activist industrial policy.[1] Indeed, policymakers across the political spectrum continue to show a keen interest in shaping the structure of the economy, evident in both the Trump trade war and the Biden administration's objectives of shoring up supply chains in key industries.[2] However, despite their historical and current ubiquity, credible empirical evidence on the long-term effects of industrial policies is still rare.

This paper estimates and quantifies the long-term effects of one of the best-known instances of industrial policy conducted on a national scale: the Heavy and Chemical Industry (HCI) Drive in South Korea between 1973 and 1979. We make two key contributions to the literature. First, using a natural experiment and unique historical firm-level data, we provide causal evidence of industrial policy's effect on firms' long-term performance. Second, we assess the long-term welfare effects of industrial policy in a quantitative general equilibrium heterogeneous firm framework.

Although the long-term effects of industrial policy are far from understood, econo-

[1] For example, see Krueger and Tuncer (1982) for Turkey during the 1960s; Head (1994) for steel rail industry of the US between 1885 and 1915; Irwin (2000a), and Irwin (2000b) for the iron industry of the US during the late 19th century; Kalouptsidi (2018) and Barwick et al. (2019) for the shipbuilding industry in China; Juhász (2018) for the cotton industry in France; Criscuolo et al. (2019) for the Regional Selective Assistance of the United Kingdom between 1997 and 2004; Chang (1993), Lee (1996), and Lane (2019) for the HCI Drive of South Korea during the 1970s; Rotemberg (2019) for India during the 2000s.

[2] See `https://www.whitehouse.gov/wp-content/uploads/2021/06/100-day-supply-chain-review-report.pdf`.

metric evidence remains limited for two main reasons. The first is data availability, as detailed information on these policies is difficult to obtain. Assessing the long-term effects of industrial policy requires information for the more distant past, making data collection even more challenging. The second is endogeneity. Industries or firms are not randomly targeted by the government, making it difficult to separate the causal effects of policies from confounding factors.[3] We overcome these empirical challenges by (i) constructing a novel historical panel dataset of firm-level subsidies and balance sheets, that is representative of the Korean economy and (ii) exploiting a natural experiment arising from the historical and institutional setting in which the HCI Drive took place.

South Korea's experience with industrial policy is important to understand, as it is one of the "growth-miracle" economies of the postwar era, well-known for its rapid transformation from a commodity and light manufacturing producer to a heavy manufacturing powerhouse. It has been argued that industrial policy played a central role in this transformation. However, a more complete understanding of how and how much industrial policy contributed to South Korea's development remains elusive.[4]

The main industrial policy tool employed by the Korean government during the HCI Drive was the allocation of foreign credit. Under the Foreign Capital Inducement Act, the Korean government strictly regulated domestic firms' direct financial transactions with foreign firms and only selectively allowed targeted firms to borrow from abroad. Once domestic firms got the approval to borrow internationally, the

[3] Because of these challenges, existing empirical evidence on long-term effects of industrial policy has been limited to either showing correlations at the sectoral level or focusing on a single sector or a few regions with a well-identified research design. Although the latter studies provide credible evidence, given that industrial policy is designed by policymakers at the national level, empirical evidence confined to a single sector or a few regions may provide limited scope for understanding and evaluating industrial policy at the national level.

[4] Wade (1990), Westphal (1990), Amsden (1989), and Rodrik (1995) argue that industrial policy played a significant role in shaping South Korea's development. However, many economists have been skeptical of the effectiveness of industrial policy (e.g. Baldwin, 1969; Lederman and Maloney, 2012). Lee (1996) did not find a positive correlation between sectoral TFP growth and tariff rates in South Korea during the 1970s and interpreted the correlation as the ineffectiveness of industrial policy.

Korean government guaranteed the loan, so that the targeted firms could borrow at more favorable interest rates than those prevailing domestically.[5]

We compile information from various sources to construct a dataset of foreign credit allocations and balance sheets at the firm level. The resulting data set is representative of the Korean economy and covers the universe of foreign credits allocated to each domestic firm. Once domestic firms got approval from the government, they had to report detailed information on the loan contracts and how they plan to use the allocated credit. The reported contract information is our main data source on subsidized credit. The information is hand-collected from the national historical archives and digitized.

Our research design uses two institutional features of the HCI Drive. First, the HCI Drive was suddenly initiated in 1972 and terminated in 1979 by political shocks rather than domestic economic conditions (Lane, 2019). President Nixon declared the withdrawal of the US forces from South Korea, which heavily relied on the US troops for its defense against North Korea. In response, President Park started promoting heavy and chemical industries to modernize military capabilities and become more self-reliant in national defense. The HCI Drive ended after the assassination of President Park in 1979. Second, the HCI Drive had pronounced regional variation. It targeted the southeastern part of the country and developed industrial complexes in these regions. Most of the subsidies were allocated to firms in these industrial complexes. Our research design compares the difference between firms in the HCI and non-HCI sectors in the targeted regions to the difference in the non-targeted regions.

Our main empirical finding is that temporary subsidies had a large and statisti-

[5]Indeed, Korean firms that borrowed from from abroad paid negative real interest rates. The domestic real interest rates were very high due to the underdevelopment of the financial system during the 1970s.

cally significant effect on firm sales as much as 30 years after subsidies ended. A firm receiving the average subsidy between 1973 and 1979 had a 919% larger sales growth between 1982 and 2009, amounting to a 8.6% higher annual growth rate over this period.[6]

The last exercise of the paper quantifies the long-term welfare impact of the HCI Drive. We set up a general equilibrium heterogeneous firm model and discipline it using the firm-level data and econometric estimates. The model rationalizes the reduced-form evidence on persistent effects of industrial policy through a combination of learning by doing (LBD) and financial constraints. There are two periods in the model. A firm's second-period productivity increases in its first-period quantity produced. However, in the first period firms are borrowing-constrained. Therefore, they cannot expand to the optimal scale to internalize the dynamic effects of LBD. Government subsidies in the first period relax these constraints, enabling firms to increase first period output, which in turn increases productivity in the second period through LBD. The model is tightly connected to the data. The key parameters of the model are pinned down by the reduced-form empirical estimates. The quantitative results imply that if the government had not conducted industrial policy, the welfare would have been 21-35% lower, depending on whether we assume that LBD-driven productivity benefits are permanent or temporary. Most of the total welfare effect (80-90%) is due to the long-run impact of subsidies on productivity through LBD.

Related Literature. This paper contributes to the empirical literature on industrial policy (see, among many others, Weinstein, 1995; Lee, 1996; Irwin, 2000a,b; Nunn and Trefler, 2010; Kline and Moretti, 2014; Aghion et al., 2015; Alder et al., 2016; Juhász, 2018; Criscuolo et al., 2019; Giorcelli, 2019; Lane, 2019; Rotemberg, 2019;

[6]Between 1982 and 2009, the real GDP of South Korea grew by 578%.

Fan and Zou, 2020; Hanlon, 2020). Harrison and Rodríguez-Clare (2010) provide a review of the literature, and of the conceptual underpinnings of industrial policy. We use the firm-level data that is representative of the national economy and estimate the effect of industrial policy on firms' long-term performance.[7] Lane (2019) studies South Korea's HCI Drive and also finds the persistent effect of the industrial policy of South Korea during the 1970s. While that paper's analysis is at the sectoral level, we study firm-level outcomes and exploit regional variation in South Korea's industrial policy for identification. Contemporaneous work by Kim et al. (2021) also uses similar firm-level balance sheet data to study the HCI Drive. While these authors focus on the relatively short-run impacts of the HCI Drive on misallocation and the plant size distribution, we estimate and quantify the long-run benefits of this policy.

We also contribute to the quantitative literature on industrial policy (see, among many others Head, 1994; Kalouptsidi, 2018; Barwick et al., 2019; Itskhoki and Moll, 2019; Liu, 2019; Bartelme et al., 2020; Lashkaripour and Lugovskyy, 2020; Buera et al., 2021). Our model rationalizes the persistent effect of industrial policy through learning-by-doing and financial frictions, and uses microdata to discipline the relevant elasticities.[8]

The rest of this paper is organized as follows. Section 2.2 describes the data. Section 2.3 presents an overview of the historical background of South Korea's industrial policy between 1973 and 1979 and discusses the natural experiment used for identification. Section 2.4 presents the estimation results. Section 2.5 builds a quantitative model consistent with the empirical findings, and quantifies the welfare benefits of

[7] While we share the focus on firm-level outcomes with Aghion et al. (2015), Criscuolo et al. (2019), and Rotemberg (2019), we contribute causal estimates of the effect of industrial policies on firms' long-term performance. Giorcelli (2019) studies the long-term effect of the government's policy on managerial training.

[8] Learning-by-doing that is external to firms has been studied in the theoretical trade literature (Arrow, 1962; Krugman, 1987; Young, 1991; Matsuyama, 1992; Melitz, 2005). However, learning-by-doing in our model is internal to firms.

the policy. Section 2.6 concludes.

2.2 Data

This section describes the construction of the data set used for the empirical and quantitative analyses. The final dataset combines firm balance sheet data, firm-level subsidy data, and region- and sector-level variables. The data set is annual and covers the period 1970 to 2012. There are 56 regions and 9 manufacturing sectors, 4 of which are classified as HCI sectors.[9] Data construction is described in detail in Appendix A.1.

Firm Balance Sheets. The firm balance sheet data come from three sources. For the sample period between 1970 and 1982, the information is digitized from the historical Annual Report of Korean Companies published by the Korea Productivity Center. For the period between 1982 and 2012, the data come from KIS-VALUE and FnGuide, which covers firms with assets above 3 billion Korean Won (2.65lmn 2015 USD).[10] We merge the two balance sheet datasets based on firm names. The variables include sales, assets, fixed assets, employment, and locations of establishments. We also supplement our data with chaebol status obtained from the the Center for Economic Catch-Up (CEC).[11]

Foreign Credit. The Foreign Capital Inducement Act required firms to report detailed information on financial contracts with foreign banks or companies once they get government approval. These reports are our main data source for foreign credit

[9]The 9 manufacturing sectors are chemicals, electronics, metals, machinery, food, textiles, wood, non-metallic mineral, and pharmaceuticals. Chemicals, electronics, metals, and machinery are classified as HCI sectors (Lane, 2019). Industry classification is in International Standard Industrial Classification of All Economic Activities (ISIC) Rev.3. 2-digit or 3-digit codes are aggregated up to 10 broad sectors. See Appendix Table B.3 of more detail.

[10]KIS-VALUE and FnGuide cover firms that are either publicly traded or subject to external audit. The 1981 Act on External Audit of Joint-Stock Corporations requires the Korean firms with assets above 3 billion Korean Won to report balance sheet information.

[11]See Center for Economic Catch-up (2007, 2008) for more detailed descriptions of these data.

Table 2.1: Descriptive Statistics of Foreign Credit Contracts

	(1) Loan Size (mln 2015 USD)	(2) Repayment Period (years)	(3) Interest Rate (%)
Mean	48.6	5.99	9.50
Std.	76.6	2.22	2.22

Notes. This table reports the descriptive statistics of approved financial contracts between domestic firms and foreign entities from 1973 to 1979. There are 538 contracts over this period, $N = 538$.

allocation. The documents have detailed information on amounts borrowed, interest rate, repayment period, and the names of foreign banks for each financial contract made by a domestic firm. These variables are hand-collected from the National Archives of Korea.[12] The constructed data set covers the universe of credit allocated to firms between 1966 and 1982, covering the HCI Drive period. The foreign credit data are merged with the firm-level balance sheet variables based on firm names.

Other Regional and Sectoral Data. Trade data come from Feenstra et al. (2005), which covers the sample period between 1966 and 2000. South Korea's import tariff data are digitized from Luedde-Neurath (1986). Input-Output tables are obtained from the Bank of Korea.

Descriptive Statistics. Table 2.1 reports the descriptive statistics for the loan contracts between 1973 and 1979 digitized from the archives. Between 1973 and 1979, there are 538 contracts. The average size of the foreign loan is \$47M 2015 USD, average repayment period was around 6.17 years, and the average interest rate was around 9%.[13] The average interest is much lower than the average deposit rate around the same time, which was around 20%.[14]

[12] Examples of the digitized financial contract documents are reproduced in Appendix Figures B.1, B.2, and B.3.
[13] Appendix Table B.1 reports additional descriptive statistics of the credit data.
[14] Because of the underdevelopment of the financial system, many firms had to rely on illegal underground markets whose average interest rate was around 40%.

Table 2.2: Descriptive Statistics Firm Balance Sheet Data

	(1) Sales (mln 2015 USD)	(2) Employment (thousands)	(3) Credit/Sales $\vert$Credit>0	(4) Ever Received Credit (fraction)
Average	89.84	1.02	0.16	0.09
Std.	278.76	1.98	0.45	

Notes. This table reports the descriptive statistics for the firm-level balance sheet data and credit. The sample is firm-years. "Credit/Sale" is the ratio of credit to sales for firm-year observations with positive amounts of credit. "Ever Received Credit" is the share of firm-year observations who ever reported positive amounts of credit between 1973 and 1979.

Table 2.2 reports the descriptive statistics of the firm balance sheet variables. Columns 1 and 2 report the average sales and employment. Column 3 reports the ratio between allocated credit and sales once a firm reports a positive amount of credit. The total credit received is sizable, about 0.16 times total sales on average. Column 4 reports the share of firm-year observations that received credit in the total observations between 1973 and 1979. About 9% of firms in the dataset ever received credit. The data set is representative of the national economy.[15]

2.3 Historical Background and Identification Strategy

The Korean government initiated the Heavy and Chemical Industry (HCI) Drive in late 1972. The HCI Drive strongly promoted six targeted sectors: steel, non-ferrous metal, electronics, machinery, chemicals, and shipbuilding. We will call these sectors the HCI sectors. The HCI Drive was temporary, ending after the assassination of President Park in 1979. During the HCI Drive, the structure of the Korean economy fundamentally changed. South Korea transformed itself from a commodity and light manufacturing producer into a heavy manufacturing producer. Between 1973 and 1979, the average annual real GDP growth rate of South Korea was 10.3%, and the average export growth rate was around 28%. The HCI sectors increased their share of

[15] On average, the sum of firms' sales in each sector covers 75% of gross output of the sector reported in the Input-Output tables published by Bank of Korea. Coverage by sector is reported in Appendix Figure B.4.

manufacturing output from 40% to 56% and their share of total exports from 12.9% to 37%.

Main Policy Instrument: Foreign Credit Allocation. The main industrial policy instrument used by the Korean government was directed foreign credit (Jones and Sakong, 1980; Amsden, 1989; Rodrik, 1995). The government used its discretionary power to allocate foreign credit toward targeted firms in the HCI sectors.[16] Through the Foreign Capital Inducement Act, first enacted in 1962, the Korean government restricted firms' direct foreign financial transactions to prevent deterioration of its balance of payments. However, once the government granted access to foreign credit to targeted firms, the government guaranteed those loans. The government guarantees eliminated the risks of firm default and the exchange rate depreciation. As a result, these firms could borrow at favorable – in fact, negative real – interest rates.[17] Domestic interest rates were much higher than foreign market interest rates because of the underdevelopment of the financial system. The average interest rate on foreign credits was around 10%, while the average deposit rate in domestic banks was around 20%. Thus, these guaranteed foreign loans constituted a subsidy.

Between 1973 and 1979, the total credits provided this way to the manufacturing firms were about \$16bln 2015 US dollars, or 11.4% of the 1972 South Korean real GDP (\$101B). This implies that the HCI Drive was a large-scale industrial policy at the national level. Firms used these allocated credits to purchase capital equipment

[16]The government nationalized the commercial banks from 1961 until the 1980s. In 1961, the Park Military Government enacted the Law for Dealing with Illicit Wealth Accumulation and ended private ownership of banks, which were deemed a part of accumulated illicit wealth. Since then, only a small fraction of banks' shares were sold publicly, and most of the shares were owned by the government, ranging from 35% to 60% during the 1970s. Also, the Temporary Law on Financial Institutions, enacted in 1961, precluded anyone from voting with more than 10% of shares of banks. Through the nationalization of the commercial banks, the government could control the lending practices and decide which industries or firms received credit. See Amsden (1989, p. 72-73) and Jones and Sakong (1980, p. 103).

[17]The Korea Development Bank, the Korea Exchange Bank, or the commercial banks controlled by the government guaranteed for foreign credit contracts. For example, Appendix Figure B.3 is the first page of the official contract between Hyundai International Inc, the domestic firm, and several foreign banks. It shows that the Korea Development Bank formally participated in the credit contract as a guarantor.

and/or adopt new advanced technology.

2.3.1 Identifying Variation

This section describes the historical background of the HCI Drive, whose features justify the identification strategy in the econometric estimation. Our identification relies on combining time series, cross-sectoral, and cross-regional variation. First, the sectoral choices of the government and the timing of the HCI Drive were driven by the external political shocks rather than the economic environment (Lane, 2019). Second, the HCI Drive was a place-based policy that disproportionately subsidized HCI sector firms in the targeted regions.

External Political Shocks. The HCI Drive was precipitated by political shocks experienced by South Korea in the late 1960s and early 1970s. The foreign shock was the 1969 Nixon Doctrine, which altered the US foreign and defense policies with respect to Asian countries. In the doctrine, President Nixon declared that the US would restrict its military actions in Asia, and that the Asian allies should take primary responsibility for their self-defense instead of relying excessively on the US.[18] In line with the new US foreign policy, Nixon set up a plan for the full withdrawal of the US forces from South Korea. Although the full withdrawal was not implemented, by early 1971 Nixon removed one-third of US soldiers present in South Korea.[19] However, at the same time, the military tension between South Korea and communist North Korea was rising.[20] South Korea lagged behind North Korea in the size of the

[18] In Guam on July 25, 1969, President Nixon said "*...in cases involving other types of aggression, we shall furnish military and economic assistance when requested in accordance with our treaty commitments. But we shall look to the nation directly threatened to assume the primary responsibility of providing the manpower for its defense...*"

[19] Nixon removed a division of 20,000 soldiers, decreasing the total US force levels to in South Korea 42,000.

[20] The South Korean government sent about 326,000 soldiers to the Vietnam war between 1964 and 1973. In exchange for South Korea's support in that war, the Johnson administration provided economic and military support to South Korea. North Korea felt threatened by the tighter bonds between the US and South Korea, increased investments in military forces, and escalated military provocations against South Korea. For example, in January 1968 North Korea sent 31 commandos to assassinate President Park. Although the attempt failed, it resulted in 31 casualties and shocked the South Korean government.

military, necessitating heavy reliance on the US forces for national defense against North Korea.[21] The establishment of official diplomatic relations between the US and People's Republic of China, which fought against South Korea in the Korean War, further raised South Korean government's level of national security concern (Nixon, 1967).

Faced with the Nixon Doctrine, in late 1972 President Park's administration decided to pursue a self-reliant defense strategy. Achieving it required modernization of military weapons, which necessitated the development of the HCI sectors. Therefore, the government embarked on the HCI Drive.

Place-Based Policy. The HCI Drive was place-based. The government picked nine southeastern regions of the country (Industrial Sites Development Corporation, 1978, p. 28).[22] In these targeted regions, the government developed industrial complexes and disproportionately subsidized firms in these complexes. Panel A of Figure 2.1 highlights the targeted regions on the map of South Korea.[23] Panel B of Figure 2.1 illustrates the geographic distribution of allocated foreign credit, concentrated in the southeastern region, and shows substantial though imperfect overlap with the set of targeted regions.

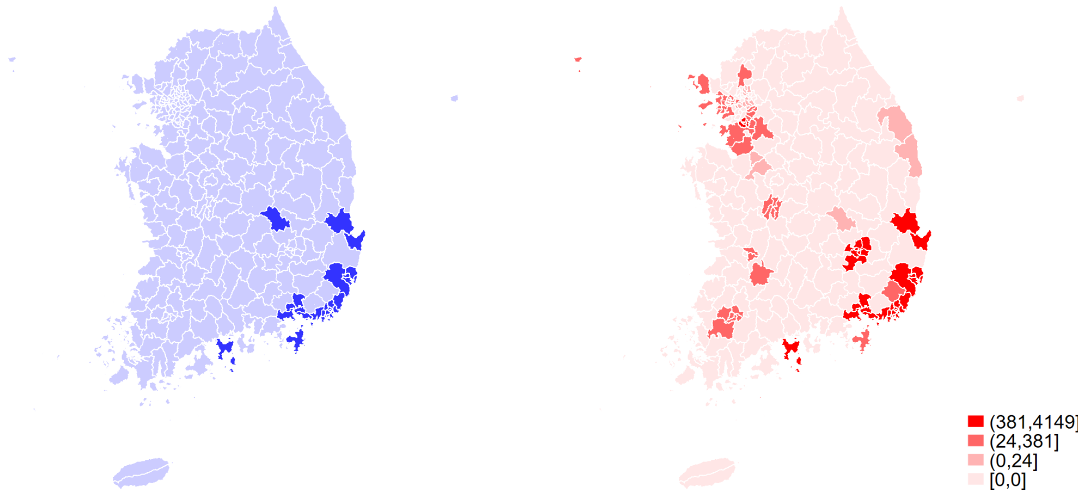
Figure 2.2 plots the distribution of credit across sectors and regions. Panel A shows total credit allocated to the HCI sector firms in targeted and non-targeted regions.

[21] South Korea's economic backwardness relative to North Korea restricted South Korea's military expenditures. According to the estimates from the Bank of Korea, South Korea's real GNP per capita was below North Korea's until the mid-1970s. In 1972, North Korea's annual military expenditures were about 100% larger than those of South Korea (Moon and Lee, 2009). Only after the late 1970s did South Korea's military expenditures surpass North Korea's.

[22] The targeted regions are Busan, Changwon, Guje, Gumi, Jinhae, Masan, Pohang, Ulsan, and Yeosu (Yeocheon). To support the building up of the manufacturing base in these regions, the Industrial Site Development Promotion Law was enacted in 1973. The industrial complexes in Changwon and Guje were newly constructed after 1973. In other regions, the existing industrial infrastructure was expanded (see Enos and Park, 1988, p. 36). Each industrial complex has its specialized sector. See Appendix Table B.2 for more on these targeted regions and complexes.

[23] One of the main reasons why these were targeted is their geographical proximity to the main port in Busan. Two main ports in Korea are Incheon and Busan. Incheon is located in the northwest, and Busan in the southeast of the country.

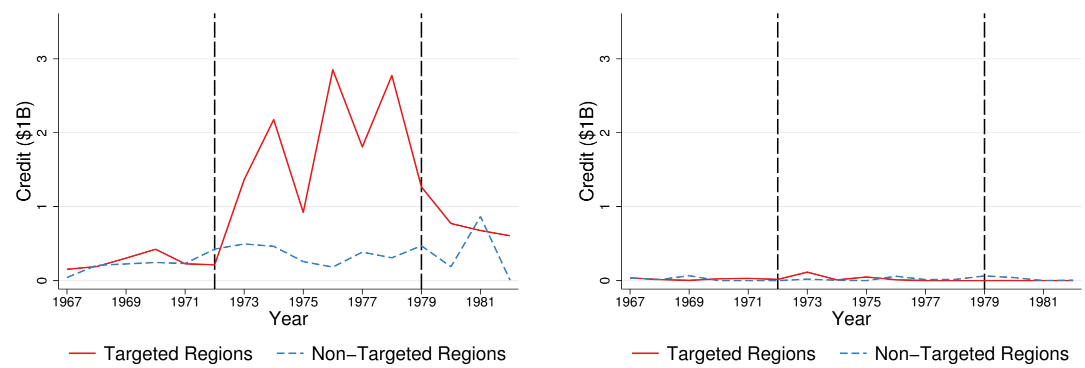
Figure 2.1: Targeted Regions and Foreign Credit Allocations



Panel A. Targeted Regions   Panel B. Foreign Credit Allocation, 1973-1979

Notes. Panel A highlights the HCI targeted regions in a darker shade. Panel B illustrates the total credit allocated to each region, in million 2015 USD.

Figure 2.2: Foreign Credit Allocation by Sector and Region



Panel A. HCI Sectors   Panel B. Non-HCI Sectors

Notes. These figures depict the amount of credit in billions 2015 US dollars in the HCI sectors (Panel A), and non-HCI sectors (Panel B). The vertical lines represent the start and the end of the HCI Drive industrial policy. The red solid and blue dashed line represent the sum of the total credits of in targeted and non-targeted regions.

After 1972, the credit going to the HCI sectors in the targeted regions dramatically increased, whereas the credit to HCI firms in the non-targeted regions rose much more modestly. Between 1973 and 1979, the total amount of credit allocated to firms in the targeted regions is about 6–7 times larger than the amount allocated to firms in the non-targeted regions on average. The figure also confirms that the industrial policy was temporary. After 1979, the HCI Drive stopped, and the total credit allocated fell. Panel B plots the sum of all the non-HCI sectors' credit in targeted and non-targeted regions. The total amount of credit allocated to firms in the non-HCI sectors is negligible compared to those in the HCI sectors. Also, there are no differential patterns between firms in targeted and non-targeted regions in the non-HCI sectors.

Figure 2.2 illustrates the identifying variation. It comes from comparing the difference between HCI sector firms in targeted and non-targeted regions and the difference between non-HCI sector firms in targeted and non-targeted regions.

2.4 Empirical Framework

To examine the effect of industrial policy on firm outcomes, we estimate the following long-difference regression model:

$$\triangle \log Sales_{fj} = \beta_1 asinh(Credit_f) + \beta_2 \log Sales_{fjt_0} + \mathbf{X'}_{fjt}\boldsymbol{\beta_3} + \delta_n + \delta_j + \epsilon_f, \tag{2.1}$$

where f denotes firm, j sector, and n region. The dependent variable $\triangle \log Sales_{fj}$ is the log change in firm sales, computed for either the 1972-1982, or the 1982-2010 period. The main independent variable, $asinh(Credit_f)$ is the inverse hyperbolic sine transformation of the sum of the total credit received by firm f between 1973 and 1979:

$$Credit_f = \sum_{\tau=1973}^{1979} Credit_{f\tau}. \tag{2.2}$$

Because a large fraction of firm observations have zero credit, we use the inverse hyperbolic sine transformation instead of logs, as suggested by Burbidge et al. (1988). This transformation allows us to include observations with zero credit, while approximating logs for larger values of the credit variable. All specifications include log initial sales $\log Sales_{fjt_0}$ and region and sector fixed effects δ_n and δ_j that absorb any region and sector common shocks. Some specifications control for additional observables $\mathbf{X}_{fjt}$. Long-differences estimation takes out time-invariant firm characteristics. The coefficient of interest is β_1. It captures how much subsidized credit increased firm sales growth. Standard errors are clustered at the regional level throughout.

OLS estimates of (2.1) may suffer from endogeneity because the government's credit allocation rule may depend on firms' unobservables. If the government selectively allocated foreign credit to firms with faster future productivity growth, the credits allocated will be correlated with the firms' unobserved productivity changes in the error term. To address this possibility, following the discussion in Section 2.3.1 we propose the following instrument for firm credit:

$$D_j^{HCI} \times D_n^{Target}, \tag{2.3}$$

where D_j^{HCI} is a dummy variable that takes on a value of 1 if a firm is in a sector targeted by the HCI Drive, and D_n^{Target} is a dummy variable for whether a firm is in the targeted region. The identifying assumption is that changes in firm unobservables are uncorrelated with the IV. That is, conditional on region and sector fixed effects and the other parametric controls, there were no shocks affecting differentially HCI sector firms in targeted regions.

Another potential source of bias is the sorting of new entrants. After the HCI Drive began, new firms with higher productivity may systematically enter the targeted region. This kind of positive sorting of faster-growing firms into the targeted regions may confound our estimates. Therefore, for both short-run and long-run analyses, we restrict our sample of firms to those that were already operating before the HCI Drive started.

To use the data more efficiently, we employ overlapping long differences. Because standard errors are clustered at the regional level, this is innocuous. We use two 7-

year long-run differences for the short-run analysis: 1972-1981 and 1973-1982. For the long-run analysis, we use 28-year long-run differences: 1981-2009 and 1982-2010.[24] The dummies for each set of differences are included in the specifications.

2.4.1 Baseline Results

Table 2.3 presents the short-run estimated coefficients, in which the outcome variable is sales growth during and immediately after the HCI Drive, 1972-1982. Table 2.4 reports the long-run effects, where the outcome variable is sales growth from 1981 of 1982 (after the HCI Drive ended) to 2009 or 2010. The tables have identical structure. Column 1 reports the OLS estimates. The coefficients are significantly positive in both the short and long run. Column 2 presents the baseline second-stage IV estimates. The coefficients become larger. The IV estimate implies that one standard deviation increase of $asinh(credit)$ increases a firm's growth rate by 0.9 standard deviations between 1973 and 1982.[25] The Kleibergen-Papp F-statistic of over 30 indicates that the instrument is strong. Column 3 reports the reduced-form estimate that directly uses the IV as a regressor. The estimated coefficient implies that sales growth of the HCI sector firms in the targeted regions was 102% higher on average than the firms in the control group. The first stage results are reported in Appendix Tables B.4 and B.5.

Table 2.4 show continuing effects in the long run. The IV estimate in column 2 implies that a one standard deviation increase of $asinh(Credit)$ increases firms' sales growth by 2.7 standard deviations.

[24] One may be concerned that if very long-term contracts were made, the 2009 or 2010 sales might be affected directly by such long-term contracts. However, average repayment period was 8.9 years, so after 30 years subsidies no longer directly affect sales.

[25] The standard deviation of $asinh(Credit)$ is around 6.4 for both the short-run and the long-run. The standard deviation of sales growth is 1.36 for the short-run and 1.66 for the long run.

Table 2.3: Short-Run Effects of Subsidies on Firm Sales Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\triangle \log Sales_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
$asinh(Credit)$	0.06***	0.18***		0.17***	0.18***	0.17***	0.17***	0.17***
	(0.01)	(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
IV			0.98***					
			(0.18)					
$\log(Sales_{t_0})$	–0.53***	–0.68***	–0.47***	–0.69***	–0.68***	–0.68***	–0.67***	–0.69***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
$Chaebol$				0.25				0.25
				(0.40)				(0.38)
$\triangle Export\ Demand \times Port$					–0.00			0.11
					(0.07)			(0.08)
$\triangle \log(Import\ Tariff) \times Port$						0.84		–6.21
						(2.19)		(8.70)
$\triangle \log(Input\ Tariff) \times Port$							3.16	19.43
							(3.83)	(15.88)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		39.19		36.80	42.16	37.91	40.11	43.06
Adj. R^2	0.45		0.39					
Num. Clusters	56	56	56	56	56	56	56	56
N	764	764	764	764	764	764	764	764

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1972 and 1981 or between 1973 and 1982. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle Export\ Demand \times Port$ is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle Import\ Tariff \times Port$ is the interaction between changes of import tariffs and the port dummy variable. $\triangle Import\ Tariff \times Port$ is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table 2.4: Long-Run Effects of Subsidies on Firm Sales Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	$\triangle \log Sales_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
$asinh(Credit)$	0.02**	0.50***		0.49***	0.47***	0.49***	0.48***	0.47***
	(0.01)	(0.13)		(0.13)	(0.11)	(0.13)	(0.12)	(0.12)
IV			1.58***					
			(0.17)					
$log(Sales_{it_0})$	–0.13**	–1.09***	–0.13**	–0.99***	–1.05***	–1.08***	–1.05***	–0.95***
	(0.05)	(0.31)	(0.05)	(0.27)	(0.26)	(0.30)	(0.28)	(0.26)
Chaebol				–1.38				–1.31
				(1.53)				(1.31)
$\triangle$*Export Demand* $\times$ *Port*					–0.19			0.22
					(0.26)			(0.30)
$\triangle$ log(*Import Tariff*) $\times$ *Port*						6.33		–10.01
						(5.98)		(27.21)
$\triangle$ log(*Input Tariff*) $\times$ *Port*							16.05	42.22
							(9.83)	(47.64)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		14.34		14.24	20.34	15.71	17.17	20.55
Adj. R^2	0.15		0.17					
Num. Clusters	54	54	54	54	54	54	54	54
N	738	738	738	738	738	738	738	738

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). log($Sales_{t_0}$) is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

2.4.2 Robustness

Chaebol Status. One special feature of the Korean economy is that large business groups, chaebols, account for a large fraction of the GDP.[26] Chaebol is a large industrial conglomerate owned and run by a business family.[27] They were inherently different from other medium or small-sized firms in many dimensions. Chaebols were not only larger but also had a closer political connection with the government. In column 4 of Table 2.3 and 2.4, we control for a dummy variable if a firm is affiliated with the top 30 chaebols.[28] Both short-run and long-run coefficients are similar to the baseline results in column 2.

International Trade. After President Park started his first term in 1962, Korea strongly promoted export-oriented development (Westphal, 1990). Given that the targeted regions are located near one of the big ports in Korea, one might be concerned about trade-related shocks correlated with the IV. If confounding factors related to trade differentially affect the targeted regions relative to non-targeted regions, it would be a threat to identification. To show that these factors do not drive our results, we additionally control for trade-related variables.

First, we control for the interaction between the port dummies and export demand shocks. Consider the following variable:

$$\frac{\triangle EX_{jt}^{KOR}}{GO_{j,1970}^{KOR}} \times Port_n, \tag{2.4}$$

where $Port_n$ is a dummy that equals one if a region has its own port, $\triangle EX_{jt}^{KOR}$ is the change in South Korea's sector j exports to the world between 1973 and

[26] In the mid-1980s, the top 10 chaebols accounted for 70% of the total GDP.

[27] Chaebol is similar to zaibatsu, Japan's business group during the prewar period. The one key difference is whether a business group could run its affiliated banks. The zaibatsu in Japan could run their affiliated banks, which were their main source of capital. However, chaebols in Korea could not own their banks, so foreign credit allocation was an important source of capital for chaebols.

[28] The top 30 chaebol groups are listed in Appendix B.1.3.

1979, and $GO^{KOR}_{j,1970}$ is sector j's gross output in 1970.[29] Changes of export intensity $\triangle EX^{KOR}_{jt}/GO^{KOR}_{j,1970}$ capture the world demand shocks for South Korea's sector j goods. The interaction term captures the possibly heterogeneous effect of the world demand shocks across regions with and without ports. However, $\triangle EX^{KOR}_{jt}$ contains not only world demand shocks but also South Korea's supply shock of sector j, which can be correlated with unobservable productivity shocks in the error terms in Equation (2.1). Therefore, instead of controlling for EX^{KOR}_{jt} directly, we control for

$$\frac{\triangle EX^{TWN}_{jt}}{GO^{KOR}_{j,1970}} \times Port_n, \tag{2.5}$$

where $\triangle EX^{TWN}_{jt}$ is the change in Taiwan's exports to the world other than Korea. This amounts to controlling for the exogenous component of (2.4) as a reduced form.[30] Because Taiwan and South Korea were industrialized during a similar period, their industry structure and exports growth are similar to each other, thus $\triangle EX_{jt}$ and $\triangle EX^{TWN}_{jt}$ are highly correlated with each other. The export shock does not suffer from the endogeneity problem if Taiwan's supply shocks are uncorrelated with the error terms in the second-stage regression. Also, note that common effects of changes of world demands are absorbed by sector effects.

Changes in import tariffs also may differentially affect the intensity of foreign competition across regions with and without ports. Because foreign competitors do not have to incur additional within-country trade costs when selling their products in regions with ports, with lower import tariffs they may have larger cost advantages than when selling in regions without ports. We control for the interaction term

[29] Busan, Changwon, Guje, Goonsan, Incheon, Masan, Mokpo, Pohang, Ulsan, and Yeosu (Yeocheon) are defined to have a port.

[30] Appendix Tables B.6 and B.7 report the IV estimates where (2.4) is the regressor instrumented with (2.5). In some specifications, the F-statistics are lower than 10, implying possibly weak instruments. However, the estimated coefficients are similar to those reported in Tables 2.3 and 2.4. Appendix Figure B.5 graphically illustrates that export intensity of Korea $\triangle EX^{KOR}_{jt}/GO^{KOR}_{j,1970}$ and export intensity measured by Taiwan's exports $\triangle EX^{TWN}_{jt}/GO^{KOR}_{j,1970}$ are highly correlated.

between the import tariffs interacted with the port dummies:

$$\triangle \log \text{Import Tariffs}_{jt} \times Port_n, \tag{2.6}$$

which allows firms in regions with ports to experience differential impacts of changes of import tariffs.

We also control for the interaction between the changes of input tariffs and the port dummies. Input tariffs may affect firms' performance through domestic firms' intermediate input usage (Goldberg et al., 2010; Halpern et al., 2015). We construct input tariffs as

$$\text{Input Tariffs}_{jt} = \sum_k \gamma^k_{j,1970} \times \mathit{Import\ Tariffs}_{kt}, \tag{2.7}$$

where $\gamma^k_{j,1970}$ is value share of input k in sector j in 1970.

The results are reported in columns 5, 6, and 7 of Tables 2.3 and 2.4. In column 8, we jointly control for all three trade-related variables. In both short-run and long-run estimations, the coefficients are within a standard error of the baseline results in column 2. The estimated coefficients for the export shocks, import tariffs, and input tariffs are statistically insignificant.

Placebo Test. Our empirical strategy compares the difference between non-HCI sector firms in the targeted and non-targeted regions to the difference between HCI sector firms in the targeted and non-targeted regions. Any common unobservables of HCI sector firms in the targeted regions may bias our estimates. For example, if the Korean government selected regions expected to have higher productivity growth in HCI sectors, this may bias our IV estimates. Another concern would be policies other than credit, applied differentially to HCI firms in the targeted regions.

To assess whether the results are driven by confounding factors at the region-sector level, we conduct a placebo test. We run the regression (2.1) with the pre-treatment

– from 1970 to 1973 – sales growth as the dependent variable. If the results were driven by confounding factors correlated with the IV, and those confounding factors were already present prior to 1973, the IV or allocated credit would be correlated with sales growth between 1970 and 1973.

Table 2.5 reports the results of the placebo test. In columns 1 and 2, the main independent variables are $asinh(Credit)$, and in columns 3 and 4, the main independent variables are the IV. In columns 5 and 6, we report the IV estimates. In columns 2, 4, and 6, we additionally control for the Chaebol status variable and trade-related variables. Across the specifications, the estimated coefficients on the main independent variables are statistically indistinguishable from zero, supporting our identifying assumption.[31]

Additional Robustness Checks. All specifications include the log of initial sales.[32] This is our preferred specification because it additionally controls for any other channels that potentially affect firms' long-run performance through initial size. The results without controlling for the initial sales are reported in Appendix Tables B.8 and B.9. The results are robust to omitting the initial size control.

We run the same regression with alternative dependent variables: log of employment and TFP. TFP is computed assuming a value-added Cobb-Douglas production function and using the method proposed by Ackerberg et al. (2015). By relying on the timing assumption of input choices, the TFP measure obtained from the production function estimation method of Ackerberg et al. (2015) addresses input choice endo-

[31] Appendix Section B.2.1 conducts an additional placebo test at the regional level with a different data set. Using regional information on manufacturing employment shares from the population census, we run a regression of growth of manufacturing employment shares between 1966 and 1970 and between 1970 and 1985 on total credit allocated at the regional level to the HCI sector firms. The results, reported in Appendix Table B.22, are consistent with results in Table 2.5. We find that the regional total credit is only positively correlated with the growth of manufacturing employment shares between 1970 and 1985, but not with the growth between 1966 and 1970.

[32] The short-run specification between 1972 and 1981 controls for 1972 sales, and between 1973 and 1982, for 1973 sales. The long-run specification between 1981 and 2009 controls for 1981 sales, and for the long difference between 1982 and 2010, controls for 1981 sales.

Table 2.5: Robustness. Placebo Test

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	$\triangle \log(Sales)$: 1970 and 1973					
	OLS		Reduced Form		IV	
$asinh(Credit)$	–0.01	–0.01			–0.06	–0.04
	(0.01)	(0.01)			(0.04)	(0.03)
IV			–0.31*	–0.26		
			(0.18)	(0.20)		
Firm Controls	N	Y	N	Y	N	Y
Region FE	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y
KP-F					17.16	25.24
Adj. R^2	0.03	0.02	0.02	0.02		
Num. Clusters	34	34	34	34	34	34
N	239	239	239	239	239	239

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the placebo results. The dependent variable is the log sales growth rate between 1970 and 1973. Columns 1-2 report the OLS estimates Columns 3 and 4 report the reduced form, where the main independent variable is the IV defined in (2.3). In columns 2, 4, and 6 control for a dummy variable of Chaebol status and the interaction term between the port dummies and export demand shocks, import tariffs, and input tariffs. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

geneity.[33] Firm value added is calculated as firm sales multiplied with value-added shares obtained from IO tables. The results are reported in Appendix Tables B.10 and B.11 for log employment and B.12 and B.13 for TFP.[34] We obtain qualitatively similar results for these alternative variables.

Instead of using the inverse hyperbolic sine transformation, we also use log of one plus credit and a dummy variable which equals one if a firm was ever allocated foreign credit between 1973 and 1979. Appendix Tables B.14 and B.15 report the results for the positive credit dummy, and Appendix Tables B.16 and B.17 report the results for log one plus credit.

Instead of using the overlapping differences, the results when using only a single

[33] To apply the method of Ackerberg et al. (2015), we need information on material inputs. For the samples between 1970 and 1982, the material input information is not available. Therefore, we first estimate the production function for the sample between 1982 and 1990 and obtain the coefficients of labor and capital. Using these estimated coefficients, we obtain TFP measures as the residuals for the sample between 1970 and 1982.

[34] The results are robust to applying different production function estimation methods.

difference are reported in Appendix Tables B.18 and B.19. To examine whether the particular choice of years is driving our long-run results, we use sales growth between 1982 and 1999 and sales growth between 1982 and 2005 as dependent variables. The results are reported in Appendix Tables B.20 and B.21. Appendix Figure B.6 reports the yearly estimates for the yearly differential sales growth between 1982 and 2011. The estimated coefficients increase as time passes.

Omitted Policies. Even if the interaction term between dummies of the targeted regions and targeted sectors is uncorrelated with omitted productivity or demand shocks, the exclusion restriction may not hold if other policies favored firms in the targeted region and sectors. In this case, our estimates would be biased upward. Although controlling for sector fixed effects may mitigate this bias by absorbing common policy components within sector, given the limited availability of other policy variables, we cannot completely rule out this possibility. However, narrative evidence suggests that this is not a major concern because the other policies were conditioned on getting approvals for foreign credit. For example, under the Foreign Capital Inducement Act, tax privileges such as exemption from acquisition or property taxes were only granted to imported foreign capital or raw materials purchased using the approved foreign credit.[35] Even if omitted policy factors induce bias in our IV estimates, our reduced-form estimates in columns 3 of Tables 2.3 and 2.4 still capture the average benefits of receiving the bundle of favorable treatments associated with receiving credit, and show that the average benefits were substantial in both the short and the long run.

[35] See Lee (1980) and Enos and Park (1988, p. 35).

2.5 Quantitative Framework

Our main empirical finding is that subsidized credit during the HCI Drive increased firm sales as much as 30 years after the credit stopped. We interpret this as evidence that this temporary policy had persistent long-run effects. This section develops a theoretical framework that captures this pattern and uses it to quantify the long-run welfare benefits of this temporary industrial policy. The main mechanism in the model is learning-by-doing (LBD) within the firm: a firm's current production experience increases its future productivity (Arrow, 1962; Krugman, 1987; Matsuyama, 1992). Firms are also borrowing-constrained. Thus, they cannot expand in the short run to internalize the future benefits of producing more today. These features are consistent with both the formal econometric, as well as narrative historical evidence.[36] In this environment, industrial policy has a role. Government subsidies relax firms' borrowing constraints and increase output in the first period, leading to productivity gains from LBD. We discipline the model by deriving the estimation equation used in the empirical analysis, allowing key parameters of the model to be recovered from the econometric estimates.

2.5.1 Model

Preliminaries. We consider a small open economy where the world is divided into Home and Foreign. There are two periods with time indexed by $t = 1, 2$. There

[36] One episode illustrates the underdevelopment of the financial system in Korea during the 1970s. Many Korean firms heavily relied on the domestic informal loan market to borrow for investment and working capital. In 1971, the collapse of the Bretton Woods system and the end the convertibility of dollars into gold resulted in a worldwide economic downturn and a sharp increase in the cost of debt financing of the Korean firms. The average deposit rate of the commercial banks was around 20%, and the average interest rate in the unofficial capital market was 30–40%. Instead of allowing financially troubled firms go bankrupt, the government bailed them out. A Presidential Emergency Decree of August 1972 nullified all the contracts between lenders and borrowers in the informal loan market. The goals of the decree were to bail out firms with large debt burdens and move loans from the informal loan market to the formal loan market. The decree required firms to report total credit borrowed in the informal loan market. The decree also capped the interest rate on the reported contracts from the informal loan market at 8% and gave an option to lenders to convert their credit into shares of borrowing firms. The reported total amount of credit in the informal loan market was 30.1% of the national domestic credit (Cole and Park, 1980). Financial frictions in the early stage of development of East Asian countries were further studied by Song et al. (2011), Itskhoki and Moll (2019), and Liu (2019), among others.

are $\mathcal{J}$ sectors indexed by j and k, partitioned into $\mathcal{J}_M$ manufacturing sectors and $\mathcal{J}_{NM}$ non-manufacturing sectors. Non-manufacturing sectors include commodities and services. Only manufacturing sectors are subject to learning-by-doing. Firms in the manufacturing sectors are monopolistically competitive and heterogeneous in terms of productivity. The non-manufacturing sectors are perfectly competitive.

Households. There are H_t households. Each household supplies one unit of labor inelastically and earns wage w_t in each period. Preferences are

$$U(\{C_t\}_{t=1,2}) = \sum_{t=1,2} \beta^{t-1} \log(C_t), \qquad C_t = \prod_{j\in\mathcal{J}} C_{jt}^{\alpha^j}$$

where β is the discount factor and C_t is consumption at time t. C_t is Cobb-Douglas with expenditure shares α^j. The ideal price index is

$$P_t = \prod_{j\in\mathcal{J}} \left(\frac{P_{jt}}{\alpha^j}\right)^{\alpha^j},$$

where P_{jt} is the price index of sector j at time t. Households' total income is $E_t = w_t H_t + \Pi_t + T_t$, where $w_t H_t$ is the labor income, Π_t is the aggregate profits of firms owned by the households, and T_t is the lump-sum tax-rebate by the government. Π_t and T_t are divided equally across households.

Sectors. The manufacturing sectors $j \in \mathcal{J}_M$ are populated by firms indexed by $f \in \mathcal{F}_j$. Home sector j output is a CES aggregate of Home firm outputs:

$$Q_{jt}^H = \left[\sum_{f\in\mathcal{F}_j} q_{fjt}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where q_{fjt} is the quantity of firm f output and σ is the elasticity of substitution across firms of sector j. The Home sectoral price index is

$$P_{jt}^H = \left[\sum_{f\in\mathcal{F}_j} p_{fjt}^{1-\sigma}\right]^{\frac{1}{1-\sigma}},$$

where p_{fjt} is firm f's price. For perfectly competitive non-manufacturing sectors $j \in \mathcal{J}_{NM}$, a representative firm prices at marginal cost, and the sectoral price index is equal to the representative firm's price: $P^H_{jt} = p_{fjt}$ for $j \in \mathcal{J}_{NM}$.

The final sector j output is a CES aggregate of Home and Foreign sector j outputs:

$$Q_{jt} = \left[(Q^H_{jt})^{\frac{\rho-1}{\rho}} + (Q^F_{jt})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where Q^F_{jt} is the quantity of Foreign sector j output demanded by Home and ρ is the elasticity of substitution across Home and Foreign sectoral outputs. The sectoral price index is

$$P_{jt} = \left[(P^H_{jt})^{1-\rho} + (P^F_{jt})^{1-\rho} \right]^{\frac{1}{1-\rho}},$$

where P^F_{jt} is the Foreign sector j price. Home takes P^F_{jt} as exogenous. In sector j the share of imports in total Home expenditure is $\pi^F_{jt} = (P^F_{jt}/P_{jt})^{1-\rho}$. Sector j in Home faces foreign demand for its output given by $Q^X_{jt} = (P^H_{jt})^{-\rho} D^F_{jt}$, where D^F_{jt} is the exogenous foreign demand. The total export revenues of Home sector j are $EX_{jt} = (P^H_{jt})^{1-\rho} D^F_{jt}$.

Firms. Firms in each sector have a Cobb-Douglas production function with constant returns to scale:

$$q_{fjt} = A_{fjt} H_{fjt}^{\gamma^H_j} \prod_k (M^k_{fjt})^{\gamma^k_j}, \qquad \gamma^H_j + \sum_k \gamma^k_j = 1,$$

where A_{fjt} is firm-specific productivity, H_{fjt} is its labor input, and M^k_{fjt} are sector k intermediate inputs used by firm f. The parameters γ^H_j and γ^k_j are common across firms within a sector. Cost minimization implies the cost of the input bundle equal to

$$c_{jt} = \left(\frac{w_t}{\gamma^H_j} \right)^{\gamma^H_j} \prod_{k \in \mathcal{J}} \left(\frac{P_{kt}}{\gamma^k_j} \right)^{\gamma^k_j}. \tag{2.8}$$

A firm in the manufacturing sector faces a downward-sloping demand curve. When a firm charges price p_{fjt}, its sales X_{fjt} are

$$X_{fjt} = \left(\frac{p_{fjt}}{P_{jt}^H}\right)^{1-\sigma} X_{jt} = \pi_{fjt} X_{jt}, \tag{2.9}$$

where X_{jt} is Home sector j's total sales, and π_{fjt} is firm f's share in sectoral sales.

Only firms in the manufacturing sectors are subject to learning-by-doing. In particular, firm f's productivities at $t = 1$ and $t = 2$ are:

$$A_{fj1} = \phi_{fj1}, \qquad A_{fj2} = \phi_{fj2}(q_{fj1})^{\xi}, \tag{2.10}$$

where ϕ_{fjt} is firm f's exogenous productivity at t. Productivity in the second period A_{fj2} is increasing in quantity produced in the first period q_{fj1}. Higher ξ implies stronger LBD. If $\xi = 0$, there is no learning-by-doing and the model collapses to the standard static multi-sector heterogeneous firm model with two periods. The value of ξ will be inferred from the econometric estimates in Section 2.4, as discussed below.

Industrial policy in the model is a proportional subsidy on firm purchases of input bundles, denoted by $\kappa_{fj1} \leq 1$. Specifically, to produce quantity q_{fj1}, the subsidized firm incurs production costs of $\kappa_{fj1}\frac{c_{j1}}{A_{fj1}}q_{fj1}$. Industrial policy is firm-specific, and only occurs in the first period.

Unconstrained Firm Problem. A firm's problem is dynamic because of LBD. Given downward sloping demand and LBD, a firm maximizes discounted profits:

$$\max_{\{p_{fjt}\}_{t=1,2}} \left\{ \underbrace{\left(p_{fj1}q_{fj1} - \kappa_{fj1}\frac{c_{j1}}{A_{fj1}}q_{fj1}\right)}_{=\Pi_{fj1}(p_{fj1})} + \beta \underbrace{\left(p_{fj2}q_{fj2} - \frac{c_{j2}}{A_{fj2}}q_{fj2}\right)}_{=\Pi_{fj2}(p_{fj1}, p_{fj2})} \right\} \tag{2.11}$$

$$\text{subject to} \quad q_{fjt} = p_{fjt}^{-\sigma}(P_{jt}^H)^{\sigma-1}X_{jt}, \quad A_{fj2} = A_{fj1}(q_{fj1})^{\xi},$$

where κ_{fj1} is a subsidy provided by the government in the first period and there is no subsidy in the second period.[37] $\Pi_{fj1}(p_{fj1})$ and $\Pi_{fj2}(p_{fj1}, p_{fj2})$ are profits in the first and the second periods. A price charged by a firm in the first period affects the second period profits, because the first period price changes the quantity produced and this quantity in turn affects productivity in the second period through LBD.

In the second period, given p_{fj1} which in turn pins down q_{fj1} and A_{fj2}, the firm's maximization problem is static. The firm charges the standard constant mark-up over marginal cost:

$$p_{fj2} = \frac{\sigma}{\sigma - 1} \frac{c_{j2}}{A_{fj2}},$$

and its sales are

$$X_{fj2} = \left(\frac{\sigma}{\sigma - 1} \frac{c_{j2}}{A_{j2}} \right)^{1-\sigma} (P_{j2}^{H})^{\sigma-1} X_{j2}.$$

Second period profits and input expenditures are $\frac{1}{\sigma} X_{fj2}$ and $\frac{\sigma-1}{\sigma} X_{fj2}$ respectively.

Given the pricing decision in the second period, a firm's maximization problem in the first period can be rewritten as

$$\Pi_{fj} = \max_{p_{fj1}} \left\{ \Pi_{fj1}(p_{fj1}) + \beta \tilde{\Pi}_{fj2}(p_{fj1}) \right\}. \tag{2.12}$$

The firm's optimal price in the first period p_{fj1}^{LBD} is the price that satisfies the first order condition of the above maximization problem: $\partial \Pi_{fj} / \partial p_{fj1} = 0$.[38] Denote the price that maximizes the first period static profits by p_{fj1}^{Static}:

$$p_{fj1}^{Static} = \frac{\sigma}{\sigma - 1} \frac{\kappa_{fj1} c_{j1}}{A_{fj1}}. \tag{2.13}$$

This is the price charged by firms in the first period when there is no LBD. Firms always set $p_{fj1}^{LBD} < p_{fj1}^{Static}$ because by dropping the price below p_{fj1}^{Static}, firms internalize LBD by increasing quantity in the first period, which in turn increases productivity in the second period.

[37] Because households own the firms, firms apply the same discount factor as the households.

[38] The mathematical derivation of the first order condition and p_{fj1}^{LBD} are described in Section B.3.1.

Constraints. Before production occurs, firms have to borrow for working capital to pay their total input expenditures. Firms face borrowing constraints in the first period, and as a result may not be able expand the first period production to reap the benefits of learning-by-doing.

We assume that the borrowing constraints take the following form:

(2.14)
$$\kappa_{fj1}(w_1 H_{fj1} + \sum_k P_{k1} M^k_{fj1}) \leq \tilde{\lambda}_{j1} A^{\sigma-1}_{fj1}, \qquad \tilde{\lambda}_{j1} = \lambda_{j1}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} c^{1-\sigma}_{j1} (P^H_{j1})^{\sigma-1} X_{j1},$$

where the left hand side of the in equality is total input costs inclusive of subsidies and the right hand side is the borrowing limit. If the total costs under the firms' optimal decision without any constraints exceed the borrowing limits, firms become constrained. The sector-specific variable $\tilde{\lambda}_{j1}$ captures tightness of borrowing constraints in sector j. It is determined in equilibrium, and is proportional to market size $(P^H_{j1})^{\sigma-1} X_{j1}$, unit cost c_{j1} and an exogenous industry-specific parameter λ_{j1}. Lower λ_{j1} implies tighter constraints. Expressing the borrowing constraint as in (2.14) is analytically convenient, and captures the notion that when firms face bad economic conditions such as increased unit cost or decreased market size, it becomes more difficult for them to borrow. Firms with higher productivity A_{fj1} are less likely to be constrained.[39] A subsidy provided by the government κ_{fj1} increases a firm's sales directly by reducing input expenditures and indirectly by relaxing the borrowing constraints.

The ratio between the exogenous constraint parameter and firm-specific subsidy $\lambda_{j1}/\kappa_{fj1}$ determines the tightness of the borrowing constraint. When $\lambda_{j1}/\kappa_{fj1} \to \infty$,

[39] Many standard models assume that firms can borrow up to $\tilde{\lambda}_{jt}\text{Assets}_{ft}$, where $\tilde{\lambda}_{jt}$ is a parameter that governs tightness of the borrowing constraints as in our model and Assets_{ft} are firm assets. This formulation of the borrowing constraint can be micro-founded using a limited commitment problem, where firm owner can steal a fraction of $1/\tilde{\lambda}_{jt}$ of total amount and lose her assets. For example, see Kiyotaki and Moore (1997), Buera and Shin (2013), Moll (2014), and Itskhoki and Moll (2019). Our borrowing constraints can also be interpreted within this standard framework, where a firm's assets are proportional to its productivity $A^{\sigma-1}_{fj1}$.

the borrowing constraints are not binding and firms set the dynamically the optimal price p_{fj1}^{LBD} that internalizes LBD. When the firm's borrowing constraint is binding, its price is pinned down by the constraint:

$$p_{fj1}^{Friction} = \frac{\sigma}{\sigma-1}\left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{-\frac{1}{\sigma}}\frac{c_{j1}}{A_{fj1}}. \tag{2.15}$$

When $\lambda_{j1}/\kappa_{fj1} < 1$, firm price is higher, and output and profits are lower than the static profit-maximizing level: $p_{fj1}^{Friction} \geq p_{fj1}^{Static} \geq p_{fj1}^{LBD}$ and $q_{fj1}^{Friction} \leq q_{fj1}^{Static} \leq q_{fj1}^{LBD}$, and the firm cannot expand its production enough to internalize learning-by-doing.[40] Only for sufficiently high λ_{j1} a firm can charge the optimal price p_{fj1}^{LBD} that fully internalizes dynamic LBD effects.

In what follows, we assume that in Korea all firms are constrained so that $\lambda_{j1}/\kappa_{fj1} \leq 1$ holds for all firms. When firms charge $p_{fj1}^{Friction}$, their revenues are

$$X_{fj1} = \left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma}{\sigma-1}\frac{c_{j1}}{A_{fj1}}\right)^{1-\sigma}(P_{j1}^{H})^{\sigma-1}X_{j1}, \tag{2.16}$$

and input expenditures are

$$c_{j1}m_{fj1} = \left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{\frac{1}{\sigma}}\frac{\sigma-1}{\sigma}X_{fj1}. \tag{2.17}$$

Total input costs inclusive of subsidy are $\kappa_{fj1}c_{j1}m_{fj1}$. First period profits equal sales minus total costs

$$\Pi_{fj1} = \left[1-\kappa_{fj1}\left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\right]X_{fj1}. \tag{2.18}$$

Sectoral sales, input expenditures, and profits sum across all firms' in the sector: $X_{jt} = \sum_{f\in\mathcal{F}_j} X_{fjt}$, $c_{jt}m_{jt} = \sum_{f\in\mathcal{F}_j} c_{jt}m_{fjt}$, and $\Pi_{jt} = \sum_{f\in\mathcal{F}_j}\Pi_{fjt}$, $\forall j,t$.

Equilibrium. Goods market clearing is

$$X_{jt} = (1-\pi_{jt}^{F})\left[\sum_{k\in\mathcal{J}_M}\gamma_k^j\sum_{f\in\mathcal{F}_k}c_{jt}m_{fjt} + \sum_{k\in\mathcal{J}_{NM}}\gamma_k^j c_{jt}m_{jt} + \alpha^j\Big(w_tH_t + \Pi_t + T_t\Big)\right] + EX_{jt},$$

[40] Appendix B.3.2 shows this formally. When $\lambda_{j1}/\kappa_{fj1} = 1$, $p_{fj1}^{Friction} = p_{fj1}^{Static}$ and $q_{fj1}^{Friction} = q_{fj1}^{Static}$.

where Π_t is aggregate profits:

$$\Pi_t = \sum_{j \in \mathcal{J}_M} \sum_{f \in \mathcal{F}_j} \Pi_{fjt},$$

and T_t is the lump-sum tax used to pay for the subsidies:

$$T_t = \sum_{j \in \mathcal{J}_M} \sum_{f \in \mathcal{F}_j} (\kappa_{fjt} - 1) c_{j1} m_{fjt}.$$

Because there are no subsidies in the second period, $T_2 = 0$. Labor market clearing implies that

$$w_t H_t = \sum_{j \in \mathcal{J}} \gamma_j^H \sum_{f \in \mathcal{F}_j} c_{jt} m_{jt}$$

The manufacturing Home price indices in the first and the second periods are

$$P_{j1}^H = \left[\sum_{f \in \mathcal{F}_j} \left((\lambda_{j1}/\kappa_{fj1})^{-\frac{1}{\sigma}} \frac{\sigma}{\sigma - 1} \frac{c_{j1}}{A_{fj1}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

and

$$P_{j2}^H = \left[\sum_{f \in \mathcal{F}_j} \left(\frac{\sigma}{\sigma - 1} \frac{c_{j2}}{A_{fj2}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

and the Home price indices of non-manufacturing sectors are $P_{jt}^H = c_{jt}/A_{jt}$ for $t = 1, 2$.

2.5.2 Counterfactuals

We are interested in the long-term aggregate welfare effects of industrial policy. Thus, our main counterfactual exercise computes the welfare change in the world in which the Korean government had not conducted industrial policy. In our model, this corresponds to setting $\kappa_{fj1} = 1$, $\forall f$.

To perform counterfactuals, we utilize a modification of the Dekle et al. (2008) exact hat algebra. Appendix B.3 describes the procedure in detail. Our modified hat algebra is composed of two parts: short- and long-run. The short-run hat algebra calculates counterfactual changes in the first period. If we feed in counterfactual subsidies into the first-period equilibrium, we obtain the short-run equilibrium allocation changes. For any outcome x, we denote counterfactual changes in the short run as $\hat{x}_1^S = x_{c,1}/x_1$, where the subscript c stands for counterfactual equilibrium allocation and superscript S stands for the short-run. The long-run hat algebra, given the short-run allocation in the first period, calculates counterfactual changes between the first and the second periods (long-run). Suppose we know a firm's long-run productivity changes A_{fj2}/A_{fj1}. We feed in these long-run shocks and calculate long-run equilibrium allocation changes. We denote long-run changes of the second period over the first period as $\hat{x}_2^L = x_2/x_1$, where the superscript L denotes long-run changes.

In our setting, changes in subsidies $\hat{\kappa}_{fj1}$ directly affect the short-run allocation in the first period and indirectly affect the long-run allocation in the second period through LBD. Although short-run allocation changes can be obtained via the standard hat algebra, computing long-run allocation changes is not straightforward because firms' long-run productivity changes are endogenous outcomes affected by the first-period quantity produced through LBD: $\hat{A}_{fj2}^L = A_{fj2}/A_{fj1} = \phi_{fj2} q_{fj1}^{\xi} / \phi_{fj1}$ where q_{fj1} depends on κ_{fj1}.

Under log utility, the welfare levels in the counterfactual equilibrium and the baseline initial equilibrium can be expressed as:

$$U_c = \left(\frac{y_{c,1}}{P_{c,1}}\right)\left(\frac{y_{c,2}}{P_{c,2}}\right)^{\beta} = \left(\frac{y_{c,1}}{P_{c,1}}\right)\left(\frac{\hat{y}_{c,2}^L}{\hat{P}_{c,2}^L}\frac{y_{c,1}}{P_{c,1}}\right)^{\beta} \tag{2.19}$$

and

$$U = \left(\frac{y_1}{P_1}\right)\left(\frac{y_2}{P_2}\right)^{\beta} = \left(\frac{y_1}{P_1}\right)\left(\frac{\hat{y}_2^L}{\hat{P}_2^L}\frac{y_1}{P_1}\right)^{\beta},$$

where c denotes counterfactual equilibrium values, and y is the per capita income.[41]

[41] Per capita income in the first period is: $y_1 = \frac{w_1 H_1 + \Pi_1 + T_1}{H_1}$. In the second period, there are no taxes/transfers ($T_2 = 0$), and the economy is unconstrained, so that total profits are a constant fraction of the wage bill. Thus the second-period per capita welfare is proportional to the real wage.

The counterfactual welfare change relative to the baseline equilibrium is

$$(2.20) \qquad \frac{U_c}{U} = \underbrace{\left(\frac{\hat{y}_1^S}{\hat{P}_1^S}\right)}_{\substack{\text{Short-run}\\\text{Welfare Change}}} \times \underbrace{\left(\frac{\tilde{y}_2^L}{\tilde{P}_2^L}\frac{\hat{y}_1^S}{\hat{P}_1^S}\right)^{\beta}}_{\substack{\text{Long-run}\\\text{Welfare Change}}} \qquad \text{where} \qquad \frac{\tilde{y}_2^L}{\tilde{P}_2^L} = \frac{\hat{y}_{c,2}^L}{\hat{P}_{c,2}^L}\Big/\frac{\hat{y}_2^L}{\hat{P}_2^L}.$$

Thus, $\tilde{x}$ denotes the ratio of long-run changes of an equilibrium variable between the counterfactual and the baseline equilibrium.[42] The overall welfare change U_c/U is composed of the short- and the long-run components.

Suppose we know the vectors of subsidy shocks $\hat{\kappa}_{fj1}^S$ and the actual long-run productivity changes $\hat{A}_{fj2}^L$. (Section 2.5.3 details the procedure for inferring these from the data). Given these two vectors, our counterfactual proceeds in three steps. In the first step, we apply the $\hat{\kappa}_{fj1}^S$ in the short-run hat algebra, and obtain the $t = 1$ counterfactual equilibrium allocation. This step gives us $\hat{y}_1^S/\hat{P}_1^S$ in (2.20). In the second step, we compute the counterfactual long-run productivity changes, which depend on the counterfactual changes of the first period quantities produced. The counterfactual long-run productivity changes are computed as

$$(2.21) \qquad \hat{A}_{c,fj2}^L = \frac{A_{c,fj2}}{A_{fj1}} = \frac{\phi_{fj2}(q_{c,fj1})^{\xi}}{\phi_{fj1}} = \underbrace{\frac{\phi_{fj2}(q_{fj1})^{\xi}}{\phi_{fj1}}}_{=\hat{A}_{fj2}^L\text{ : Data}} \times \underbrace{\left(\frac{q_{c,fj1}}{q_{fj1}}\right)^{\xi}}_{\substack{=\hat{q}_{fj1}^S\text{ : Short-run}\\\text{hat algebra}}},$$

where $\hat{A}_{fj2}^L$ will be backed out from the data, and changes of each firm's quantity produced $\hat{q}_{fj1}^S = q_{fj1}^c/q_{fj1}$ come from the short-run hat algebra in the first step.[43] In the last step, we feed in $\hat{A}_{c,fj2}^L$ and $\hat{A}_{fj2}^L$ and apply the long-run hat-algebra to the counterfactual and baseline first period short-run allocation. From the long-run hat algebra applied to the counterfactual equilibrium and the initial equilibrium,

[42] Caliendo et al. (2019) adopt a similar approach. By computing the ratio of changes, one can compute the counterfactual change without knowing the levels of the shocks. In our application, we do not require information on the initial level of each firm's quantities produced in the first period, which is used to compute long-run productivity changes.

[43] Changes in quantity produced in the short run are expressed as $\hat{q}_{fj1}^S = (\hat{c}_{j1}^S)^{-\sigma}\frac{1}{\hat{\kappa}_{fj1}^{H,S}}(\hat{P}_{j1}^S)^{\sigma-1}\hat{X}_{j1}^S$.

Table 2.6: Summary of Calibrated Parameters

Param.	Value	Description	Moment	Source
Intertemporal Discount Factor				
β	1.62	Permanent Δproductivity		
β	0.90	Temporary Δproductivity		
Elasticities				
η	0.12	Effective subsidy from credit	IV Estimates	Data
ξ	0.85	Learning by doing	IV Estimates	Data
σ	3	Elast. of subst. varieties		Broda and Weinstein (2006)
ρ	2	Elast. of subst. Home & Foreign		3
Shocks				
λ_{j1}		Financial frictions	IV Estimates	Data
$\{\hat{\kappa}^S_{f1}\}$		Subsidy shocks	IV Estimates	Data
$\{\hat{A}^L_{fj2}\}$		Long-run productivity shocks	Sales, PPI	Data, OECD STAN
$\{\hat{D}^{F,L}_{j2}\}$		Long-run Foreign demand shocks	Exports	IO table
$\{\hat{P}^{F,L}_{j2}\}$		Long-run Foreign import price shocks	Import shares	IO table
Production & Consumption				
$\{\alpha^j\}$		Final consumption shares	IO table	IO table
$\{\gamma^H_j, \gamma^k_j\}$		Labor & intermediate shares	IO table	IO table

Notes. The table summarizes the calibrated values used for the quantitative analysis.

we obtain $\hat{y}^L_{c,2}/\hat{P}^L_{c,2}$ and $\hat{y}^L_2/\hat{P}^L_2$. From these long-run changes, we compute relative changes $\tilde{y}^L_2/\tilde{P}^L_2$ in Equation (2.20). For the long-run hat-algebra, we also feed in changes in the population $\hat{H}^L_2$.

2.5.3 Taking the Model to the Data

To implement the counterfactual, we need values of subsidy shocks $\{\hat{\kappa}_{fj1}\}$, long-run productivity shocks of the observed equilibrium $\{\hat{A}^L_{fj2}\}$, long-run foreign demand and import price shocks $\{\hat{P}^{F,L}_{jt}\}$ and $\{\hat{D}^{F,L}_{jt}\}$, sectoral constraint tightness $\{\lambda_{j1}\}$, and the learning-by-doing elasticity ξ. Because each firm is an object in the model, we need the firm-specific market shares of the initial equilibrium, which we take directly from the data. The remaining parameters can be calibrated to standard values in the literature. The summary of the calibrated values is reported in Table 1.3.

Subsidies and the Learning-By-Doing Parameter. Using the short-run and long-run econometric estimates of (2.1), we back out two key parameters of the model: LBD elasticity ξ and firm-specific subsidies κ_{fj1}. We back out subsidies from the short-run sales changes and pin down ξ from the long-run response of sales to past subsidies.

Log first period firm sales are (see 2.16):

$$\log X_{fj1} = -\frac{\sigma-1}{\sigma}\log\kappa_{fj1} + C_{j1} + (\sigma-1)\log\phi_{fj1} \tag{2.22}$$

where C_{j1} absorbs industry common components. We assume that the subsidy κ_{fj1} takes the following form:

$$\kappa_{fj1} = exp\big(-\eta \times asinh(Credit_{fj1})\big). \tag{2.23}$$

From (2.22) and (2.23), we derive the following estimable short-run regression model:

$$\log X_{fj1} = \underbrace{\beta_1^S}_{=(\sigma-1/\sigma)\eta} \times asinh(Credit_{fj1}) + \delta_{n1} + \delta_{j1} + \log\phi_{fj1}, \tag{2.24}$$

where any region or sector common variables are absorbed by region-time fixed effects δ_{nt} and sector-time fixed effects δ_{jt}.[44] Unobservable firm productivity in the first period $\log\phi_{fj1}$ is a structural residual. Time-differencing, we can derive the short-run regression model as in Equation (2.1).[45] With the estimated $\hat{\beta}_1^S$ and a value of σ, we can obtain a value of η that connects the credit observed in the data to the subsidy rate in the model. With this $\hat{\eta}$, firm-specific subsidies are obtained as

$$\kappa_{fj1} = exp\big(-\eta \times asinh(Credit_{fj1})\big). \tag{2.25}$$

This procedure thus generates the firm-specific levels of the subsidy rate in the first period. We winsorize the 5% highest subsidy rates to make the results robust to outliers.

[44] δ_{jt} absorbs variables that are common within sector: sectoral constraint $\frac{\sigma-1}{\sigma}\log\lambda_{j1}$, costs of input bundles c_{j1}, and market size $(P_{j1}^H)^{\sigma-1}X_{j1}$. Although regions are not explicitly modeled in our quantitative framework, δ_{nt} absorbs factors that are common within region.

[45] Strictly speaking, of course, the model only has one first period. To take the short-run time difference inside the model, we can think of period 1 as consisting of several sub-periods identical in every way except for credit given to firms, such that we can take the time difference in sales and credit between the later and the earlier sub-periods.

From the long-run changes in firms' sales, we estimate the LBD parameter ξ. Second period firm sales can be written as:

$$\log X_{fj2} = (\sigma-1)\xi \log \kappa_{fj1} + \delta_{n2} + \delta_{j2} + (\sigma-1)\log \phi_{fj2} + \sigma \log \phi_{fj1}, \tag{2.26}$$

where δ_{n2} and δ_{j2} are region and industry common components.[46] Because of LBD, subsidies κ_{fj1} and exogenous productivity in the first period $\log \phi_{fj1}$ appear in the second period sales. Substituting (2.23) into (2.26) yields the following estimable regression model:

$$\log Sale_{fj2} = -\underbrace{\beta_1^L}_{=(\sigma-1)\xi\eta} \times asinh(Credit_{fj1}) + \delta_f + \delta_{nt} + \delta_{jt} + \epsilon_{ft}, \tag{2.27}$$

where region and sector fixed effects capture similar objects as in Equation (2.24), and firm fixed effects reflect cross-firm differences in period 1 productivity. Differencing this equation with respect to period 1 yields the long-run regression specification (2.1). Using the short-run and long-run estimates from Equations (2.24) and (2.27) and a value of σ, we can obtain the estimated ξ using the following relationship:

$$\sigma\xi = \frac{\beta_1^L}{\beta_1^S} \iff \xi = \frac{1}{\sigma}\frac{\beta_1^L}{\beta_1^S}. \tag{2.28}$$

Intuitively, the short-run regression coefficients in Table 2.3 pick up the mechanical effect of subsidies on output: giving money to firms to produce naturally increases their sales. The short-run estimates are useful for translating the amount of credit firms received into effective subsidy operating in the model. Then, long-run coefficients in Table 2.4 contain information on the strength of LBD by comparing $t=2$ sales of subsidized and non-subsidized firms.

[46] δ_{j2} is proportional to $\prod_{h=0}^{1}\left[\left(\frac{\sigma}{(\sigma-1)}c_{j,t-2}\right)^{(1-\sigma)(\sigma\xi)^h} \times ((P^H_{j,2-h})^{\sigma-1}X_{j,2-h})^{(\xi(\sigma-1))^h}\right]$.

Sectoral Constraint Tightness. The degree of sectoral financial frictions λ_{j1} is set to:

$$\lambda_{j1} = \min_{f \in \mathcal{F}_j} \{\kappa_{fj1}\},$$

which ensures that even the firm that received the largest subsidy rate (or the lowest input cost) still charges the static profit maximizing price and cannot optimally increase output to take advantage of LBD. We view this as a conservative value, because even lower values of λ_{j1} would imply firms are more constrained and therefore generate larger gains from the industrial policy. Also, this assumption simplifies the counterfactual hat algebra.

Calibration of the Remaining Parameters and Data Inputs. Firm market shares π_{fj1} are calculated as follows. We directly observe firm-level sales in 1982 in our main data set. For some observations without information on sales, we impute missing sales using assets.[47] After summing the observed firm-level sales, we calculate the residual of sectoral gross outputs by subtracting the sum of sales in the firm-level data from the gross output in the 1983 IO table. We treat the residuals as a separate firm.[48] Firm-level shares are then obtained as firms' sales divided by the gross sectoral output from the IO table. Import shares π^F_{j1} and export values EX_{j1} are obtained from the IO table in 1982.

The long-run productivity changes and foreign demand import price changes are jointly calibrated. The sales growth of firm f relative to a reference firm f_0 in the same sector gives us relative long-run productivity changes $\hat{A}^L_{fj2}/\hat{A}^L_{f_0j2}$:

$$\frac{\hat{A}^L_{fj2}}{\hat{A}^L_{f_0j2}} = \frac{1}{\sigma - 1} \frac{\triangle \log Sales_{ft}}{\triangle \log Sales_{f_0t}}.$$

[47] There are some firms without information on sales, but all firms have information on assets. Appendix B.3.4 describes the imputation procedure in detail.

[48] In our quantitative analysis, the total number of firms for each sector is the total number of firms in the firm-level data that were operating in 1982 plus one. The residuals are the sum of sales of small-sized firms that are not in our data set.

Then, we pin down the long-run productivity growth of the reference firm ($\hat{A}^L_{f_0 j2}$) and foreign demand and import price changes ($\hat{D}^{F,L}_{j2}$ and $\hat{P}^{F,L}_{j2}$) by fitting changes in the producer price index, import shares, and export values exactly between 1982 and 2010. See Appendix B.3.7 for more detail.

The model has 2 periods, so we must take some care to set an appropriate value of β between the first and the second period. The first period corresponds to roughly a decade. The second period consists of about 25 years, but the learning-by-doing benefits build slowly (Appendix Figure B.6), and our regression estimates reflect the total productivity increment at the end of the period. To be conservative, we assume that the productivity benefits accrue 15 years into the future. At that point they become permanent. Thus, assuming an annual discount rate of 0.96, the decadal discount rate is $0.96^{10} = 0.66$. If the productivity benefit comes 15 years into the future, and is permanent, then $\beta = 0.66^{1.5}/(1-0.66) = 1.62$. Alternatively, to be even more conservative we assume that the productivity benefit starts 15 years in the future and persists for only one more decade. This would be the case, for example, if there is some forgetting, or if the technologies about which LBD took place become obsolete. In that case, $\beta = 0.66^{1.5} + 0.66^{2.5} = 0.90$.

Finally, we set the elasticity of substitution σ and ρ to 3 and 2 following Broda and Weinstein (2006) and Boehm et al. (2020), respectively.

2.5.4 Welfare Results

Our main counterfactual computes the welfare change in the counterfactual world in which the Korean government did not conduct the industrial policy. We set $\kappa_{fj1} = 1$ for all firms so that no subsidies are given in the first period. The results are reported in Table 2.7. When there is no subsidy in the first period, and the productivity benefits are permanent, the overall welfare decreases by 34.86%. In this total, 3.58%

is the short-run welfare decrease, and 31.28%, or about 90%, is the long-run welfare decrease. The short-run welfare changes come from exacerbated financial frictions in the first period, while the long-run welfare changes are due to lower second-period productivity as a result of less LBD. The industrial policy has quantitatively sizable impacts in the long run, consistent with the empirical finding that subsidies have persistent effects on firms' long-term performance. When we assume the productivity benefits are temporary, the short-run welfare impact is unchanged, but the long-run welfare decrease is 17.38%. Still, it the long run accounts for 83% of the total welfare impact.

The welfare analysis above uses actual subsidies received by each firm. However, our IV strategy based on which ξ and η are calibrated does not feature a firm-level instrument. Thus, our econometric estimates cannot distinguish between the case in which only the actually subsidized firms benefited from the subsidies, and a case in which the subsidies had broader benefits to the treated group due to, for instance, agglomeration within a sector-location. To see how much this disconnect affects our results, we perform an alternative counterfactual in which we assume that subsidies were received by firms as predicted by the first stage. In this case, we are only using sector-location variation to allocate the subsidies, and all the firms within a sector location have the same propensity to receive the subsidy. Appendix B.3.9 described the procedure in detail. The bottom panel of Table 2.7 reports the results. If anything, the welfare effects are even larger under this alternative.

Appendix Table B.23 reports the results under different values of substitution elasticities σ and ρ including $\rho = 2$ (Boehm et al., 2020). Both short- and long-run gains from the subsidies decrease in σ and ρ. With higher ρ, households substitute their consumption more toward Foreign outputs in the first period when firms are

Table 2.7: Counterfactual: No Subsidy

Welfare change:	(1) Total (%)	(2) Short-run (%)	(3) Long-run (%)
Actual subsidies			
Productivity change:			
Permanent ($\beta = 1.62$)	−34.86	−3.58	−31.28
Temporary ($\beta = 0.90$)	−20.96	−3.58	−17.38
Predicted subsidies			
Productivity change:			
Permanent ($\beta = 1.62$)	−52.80	−4.25	−48.55
Temporary ($\beta = 0.90$)	−31.22	−4.25	−26.97

Notes. The table reports the welfare effects under the counterfactual in which the Korean government did not conduct the industrial policy. The top panel uses the observed subsidy to each firm. The bottom panel uses the subsidy predicted by the first-stage regression.

constrained. This dampens the negative effects of the frictions and therefore the long-run LBD gains.

2.6 Conclusion

This paper provides causal evidence of industrial policy on firms' long-term performance. We show that subsidized credit distributed to firms during the 1973-79 HCI Drive in South Korea had persistent effects on firm sales, that are evident as much as 30 years after the subsidies themselves stopped. To rationalize this empirical finding and quantify its importance, we a build a quantitative heterogeneous firm framework with learning-by-doing and financial frictions. In this environment, if the industrial policy had not been implemented, South Korea's welfare would have been noticeably lower.

CHAPTER III

Lobbying, Trade, and Misallocation

3.1 Introduction

The economic consequences of firms' political engagement have received much attention in both politics and academic research. An abundance of evidence shows that politically active firms spend large sums of money to influence the policy-making process (Roosevelt, 1910; Drutman, 2015; Zingales, 2017).[1] According to the data collected in compliance with the Lobbying Disclosure Act (1995), which requires lobbyists to report lobbying expenditures to the US Congress, firms spent \$3.51 billion on lobbying alone in 2019. Larger firms spend more on lobbying, a phenomenon that is even more pronounced with the advent of superstar firms brought on by globalization. However, it is still an open question how much lobbying affects the overall resource allocation in an economy.

This paper examines the effects of corporate lobbying on aggregate total factor productivity (TFP). It is commonly believed that lobbying decreases the aggregate TFP of an economy because resources are allocated on the basis of a firm's political connections rather than its productivity. If there are no other distortions, what is

[1] The debate over the influence of special interests on the US politics has a long history. In a speech given in Kansas in 1910, Theodore Roosevelt, the 26th president of the US, said that "*. . . Exactly as the special interests of cotton and slavery threatened our political integrity before the Civil War, so now the great special business interests too often control and corrupt the men and methods of government for their own profit. We must drive the special interests out of politics. . .*" (Roosevelt, 1910).

trivially true. Contrary to this conventional wisdom, I argue that when an economy is subject to pre-lobbying distortions, it is possible for lobbying to improve aggregate TFP.[2] By quantifying the impact of lobbying on the US aggregate TFP, I show that indeed lobbying raises aggregate TFP in the US.

I begin by setting up an open-economy heterogeneous firm model (Melitz, 2003) with misallocation manifested in firm-specific taxes/distortions (Hsieh and Klenow, 2009). Firms decide whether to pay a fixed cost to lobby the policymaker and how much to spend on lobbying to reduce its firm-specific distortion. Because of the fixed cost, not all firms lobby, and larger firms are more likely to engage in lobbying activity. I first show analytically that whether lobbying increases or decreases aggregate TFP depends on the pre-lobbying distribution of exogenous taxes/distortions across firms. The intuition for this result is that if the firms that lobby in the equilibrium face relatively higher pre-lobbying distortions, lobbying reduces those distortions and thus the equilibrium level of misallocation. When the more productive firms are more distorted, lobbying can improve TFP because these more productive firms can lobby to overcome high pre-lobbying distortions, leading to improvements in the resource allocation in an economy.[3]

The model implies that the key to quantifying the net impact of lobbying on aggregate TFP is the covariance between firm productivity and exogenous wedges driven by pre-lobbying exogenous distortions. Whether the more productive firms are subject to higher pre-lobbying distortions depends on the sign of this covariance. While I do not observe the covariance between firm productivity and exogenous wedges,

[2] The impact of lobbying on resource allocation has been studied in the previous literature. Lobbying may decrease TFP if special interests provide pecuniary benefits to policymakers in exchange for favorable policies (Krueger, 1974; Grossman and Helpman, 1994). However, lobbying can improve resource allocation by transmitting information to policymakers when the policymakers cannot observe the true state of the economy due to information frictions (Milgrom and Roberts, 1986). Grossman and Helpman (2001) summarize the literature.

[3] Size-dependent policies are one example of policies that make the more productive firms more distorted (Guner et al., 2008; Garicano et al., 2016).

the theoretical framework provides guidance on which objects observable in the data can be used to identify this covariance. Because of the complementarity between firm size and gains from a lower tax post-lobbying, lobbying expenditures increase in both productivity and exogenous wedges. Using these monotonic relationships, I show that the covariance between firm lobbying expenditures and exogenous wedges is the identifying moment for the unobservable covariance between firm productivity and exogenous wedges, which can be computed from the data. In the simpler environment, I formally show that there is a one-to-one relationship between the covariance between firm productivity and exogenous wedges and the covariance between firm lobbying expenditures and exogenous wedges.

I combine Compustat balance sheet data and firm lobbying expenditures disclosed publicly since the Lobbying Disclosure Act (1995). I estimate the parameters of the model using the instrumental variable (IV) approach and the method of moments. To estimate the parameter that governs how effectively lobbying decreases firm-specific distortions, I regress firm-specific distortions on lobbying expenditures instrumented by the state-level time-varying appointment of a Congress member as chairperson of the Appropriations Committees of House and Senate. The IV estimates imply that a 1% increase in lobbying expenditures lowers the output distortions by 0.09-0.1%. The covariance between productivity and exogenous wedges is identified by targeting the identifying moment. I calibrate the remaining parameters by matching the moments from the model to their data counterparts. Using the estimated parameters, I find that the more productive firms tend to face higher pre-lobbying distortions in the US.

To quantify the impact of lobbying on the aggregate TFP of the US, I compare the baseline US economy, where lobbying is allowed, to a counterfactual economy with the same level of pre-lobbying distortions, but where lobbying is not allowed. If lobbying were not allowed, the TFP of the US economy would be 4-7% lower.

The TFP influences of lobbying can be affected by international trade through market size effects. Because of the complementarity between market size and gains from a lower tax post-lobbying, trade opening causes non-exporters to decrease but exporters to increase lobbying expenditures. This prediction is supported by reduced-form empirical findings using the China shock (Autor et al., 2013). I find that a one standard deviation increase in the China shock led to a divergence of about 0.4 standard deviations in lobbying expenditures between firms at 25th and the 75th percentile of the size distribution. Quantitatively, I find that when opening to trade, the positive TFP gains from lobbying decrease by 0.1% compared to autarky. This is because the increased market size induced by trade causes exporters to spend more on lobbying than in autarky, reallocating to these lobbying exporters. This increased concentration of resources among exporters decreases the positive TFP gains from lobbying.

Related Literature. This paper contributes to the literature on firm-level resource misallocation pioneered by Hsieh and Klenow (2009) and Restuccia and Rogerson (2008). While many papers have examined specific factors behind resource misallocation, this paper specifically examines lobbying as a source of resource misallocation.[4] My work is most closely related to Arayavechkit et al. (2017) and Huneeus and Kim (2018) which also models to quantify the impact of lobbying on resource misallocation. In contrast to their work, I analytically characterize the conditions under which lobbying increases aggregate TFP as the second-best under firm-specific pre-lobbying

[4] Examples in the literature are Buera et al. (2011), Midrigan and Xu (2014), Moll (2014), and Gopinath et al. (2017) for financial frictions; Fajgelbaum et al. (2019) for tax; Edmond et al. (2015) for a firm's market power; Guner et al. (2008), Lafontaine and Sivadasan (2009), Petrin and Sivadasan (2013), and Garicano et al. (2016) for labor regulation.

distortions and consider the implications of lobbying in an open economy.

I also contribute to the empirical literature on corporate lobbying, including Bombardini and Trebbi (2011), Igan et al. (2012), Blanes i Vidal et al. (2012), Bertrand et al. (2014), Kerr et al. (2014), and Bertrand et al. (2020).[5] While these papers have empirically studied lobbying in the US, the quantitative implications of lobbying have been less studied. Using a novel instrumental variable approach, at the micro-level, I find large private returns to lobbying in line with the literature (Richter et al., 2009; Kang, 2016; Kim, 2017). At the macro-level, however, I find that lobbying can increase the aggregate TFP of the US. This result emphasizes the importance of understanding the general equilibrium effects of lobbying. This paper is also related to research on firm lobbying in the trade literature, including Grossman and Helpman (1994), Goldberg and Maggi (1999), Gawande and Bandyopadhyay (2000), Bombardini (2008), Bombardini and Trebbi (2012), Gawande et al. (2012), Kim (2017), and Blanga-Gubbay et al. (2020). I provide a novel empirical finding that market size changes induced by international trade lead to divergence in the lobbying practices of small- and large-sized firms.

Finally, this paper contributes to the literature that studies the impact of trade on distorted economies. Domestic distortions such as institutions, contracting frictions, and imperfect competition can affect gains from trade.[6] Unlike previous studies, this paper studies lobbying as a source of distortions and examines the joint implications of lobbying and international trade. While Berthou et al. (2018), Costa-Scottini (2018), Bai et al. (2019), and Chung (2019) examine gains from trade in the presence of firm-specific exogenous distortions, I treat distortions as an endogenous outcome

[5] Bombardini and Trebbi (2020) provides an insightful review of the recent literature.

[6] Important contributions include Levchenko (2007), Nunn (2007), Do and Levchenko (2009), Levchenko (2013) on institutions; Khandelwal et al. (2013) on state-owned enterprises; Edmond et al. (2015) on imperfect competition; Manova (2013) on financial friction.

of lobbying.

The remainder of this paper proceeds as follows. Section 3.2 outlines the quantitative model and derives the conditions under which lobbying can increase aggregate TFP. Section 3.3 discusses how the key parameters of the model are identified and quantitatively assesses the effects of lobbying on TFP and welfare. Section 3.4 presents empirical evidence on the effects of import exposure on firm lobbying behaviors and quantifies the impact of international trade on the level of misallocation through lobbying. Section 3.5 concludes the paper.

3.2 Theoretical Framework

I construct a general equilibrium heterogeneous firm model with lobbying. There are two potentially asymmetric countries, Home and Foreign, indexed by $c = H, F$. Country c is populated by L_c identical households, which supply a unit of labor inelastically and earn wage w_c. A representative consumer in country c chooses the amount of final goods consumption C_c to maximize utility subject to their budget constraint.

Final Goods Producers. A final good Q_c is produced by a representative final goods producer under perfect competition. A final goods producer combines intermediate varieties available in the country through a constant elasticity of substitution (CES) aggregator:

$$Q_c = \left[\int_{\omega \in \Omega_c \cup \Omega_c^x} q(\omega)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where each variety is denoted as ω, σ is the elasticity of substitution, and q is the quantity demanded of each variety. Ω_c and Ω_c^x are the sets of domestic and foreign varieties available in country c, which are endogenously determined in the equilibrium.

The ideal price index is

$$P_c = \left[\int_{\omega \in \Omega_c} p(\omega)^{1-\sigma} + \int_{\omega \in \Omega_c^x} p^x(\omega)^{1-\sigma} \right]^{\frac{1}{1-\sigma}},$$

where p and p^x are prices charged by domestic and foreign intermediate goods producers.

Intermediate Goods Producers and Lobbying. There is a fixed mass of monopolistically competitive intermediate goods producers M_c in country c. Labor is the only factor of input for production. The production function for each variety is

$$y(\omega) = \phi(\omega) l(\omega),$$

where y is output produced, ϕ is productivity, and l is the labor input. The production of each variety requires fixed production costs f_c in units of labor, so the total labor used for production is $y/\phi + f_c$. Intermediate goods producers can export after incurring fixed export costs f_c^x in units of domestic labor (Melitz, 2003). They also incur iceberg trade costs $\tau_x \geq 1$ when exporting, so delivering one unit of an intermediate good to a foreign country requires τ_x units. Iceberg trade costs are symmetric across countries.

Intermediate goods producers are subject to domestic output distortions τ^Y. These output distortions are interpreted as taxes in the model, so τ^Y is the firm-specific tax rate.[7] Output distortions decrease in lobbying amounts. Thus, if a producer increases its lobbying amounts, it will be taxed less or subsidized more proportionately to its revenues. I assume that output wedges induced by output distortions have the following functional form:

$$\underbrace{1 - \tau^Y(\omega)}_{\substack{\text{Output}\\ \text{wedge}}} = \underbrace{(1 - \bar{\tau}^Y(\omega))}_{\substack{\text{Exogenous}\\ \text{wedge}}} \times \underbrace{(1 + b(\omega))^{\theta}}_{\substack{\text{Endogenous}\\ \text{wedge}}},$$

[7] If $\tau^Y < 0$, firms are subsidized and if $\tau^Y > 0$, firms are taxed.

where b is lobbying amounts chosen by an intermediate goods producer and $1 - \bar{\tau}^Y$ is an exogenous wedge drawn from a given distribution. $1 - \tau^Y$ is composed of an exogenous and an endogenous wedge. The exogenous wedge $1 - \bar{\tau}^Y$ á la Hsieh and Klenow (2009) captures distortions not related to lobbying. Firms take $1 - \bar{\tau}^Y$ as given and make a lobbying decision. The endogenous wedge $(1+b)^\theta$ where b is in the units of domestic final goods is the results of lobbying. θ is one of the key parameters of the model. It captures how effectively lobbying decreases output distortions (or increases output wedges).[8] With higher values of θ, the same amount of lobbying can decrease the output distortion more. On the other hand, when $\theta = 0$, lobbying cannot affect the output distortion, so no firms participate in lobbying.

Firms incur fixed costs $f^b\eta$ to participate in lobbying, which is also in the units of domestic final goods.[9] Because of stochastic η, each firm has a different level of fixed lobbying costs.[10] A higher η indicates that firms have to pay higher fixed costs to participate in lobbying. Once a firm decides to participate in lobbying, the total lobbying cost is the sum of the variable and the fixed lobbying costs:

$$P_c(b + f^b\eta).$$

Aggregate lobbying expenditure is redistributed to domestic consumers through lump-sum transfers.[11] I impose restrictions on θ and σ as follows:[12]

[8] θ may reflect quality of institutions or political system. For example, θ will be higher in countries where corruption is prevalent.

[9] The fixed lobbying cost rationalizes the pattern in the firm-level data that only a fraction of firms (13.7% on average) participate in lobbying, which is well documented in Kerr et al. (2014).

[10] The stochastic component of the fixed lobbying cost η rationalizes the pattern in the data that some small-sized firms exhibit sizable lobbying expenditure. Although firm size and lobbying expenditures are highly correlated, firm size alone cannot fully explain lobbying behavior. Without η, firm size and lobbying expenditures are perfectly correlated. The relationship between size and lobbying expenditure is documented in greater detail in Online Appendix Section C.3. For example, a firm may have lower fixed lobbying costs (low η) if the CEO is well-connected with local politicians or a firm is located near K Street in Washington DC.

[11] This is consistent with the current lobbying market of the US, in which firms hire lobbyists to influence the policy-making process and lobbyists use their earnings to consume goods. Assuming that aggregate lobbying expenditure is redistributed back to domestic consumers, I implicitly assume that there are no resources wasted in the lobbying process. If parts of the lobbying expenditures are pure waste, there would be a larger welfare loss. For example, Esteban and Ray (2006) considers lobbying a costly signal.

[12] The parametric restrictions guarantee that firms do not spend infinite amounts on lobbying. If $1 - \theta\sigma \geq 1$, the output distortions decrease too quickly with an increase in lobbying amounts b. Technically, this is the second-order

Assumption III.1. *θ and σ satisfy (i) $0 < 1 - \theta\sigma < 1$, and (ii) $\sigma > 1$.*

Intermediate goods producers are heterogeneous along three dimensions: productivity ϕ, exogenous wedges $1 - \bar{\tau}^Y$, and stochastic fixed lobbying costs η. The firm-specific vector of shocks $(\phi, 1-\bar{\tau}^Y, \eta)$ is drawn from a joint distribution $F_c(\phi, 1-\bar{\tau}^Y, \eta)$ with an arbitrary correlation structure. Each draw is independent across firms.

An intermediate goods producer takes the demand function in domestic and foreign markets as given and maximizes its profits. An intermediate goods producer solves the following maximization problem:

$$
\begin{aligned}
(3.1) \quad \pi = \max_{b,p,p^x,q,q^x,x} & (1-\bar{\tau}^Y)(1+b)^\theta pq - \frac{w_c}{\phi}q - wf_c \\
& + x\left\{(1-\bar{\tau}^Y)(1+b)^\theta p^x q^x - \frac{w_c}{\phi}q^x - wf_c^x\right\} - P_c b - P_c f^b \eta[b>0], \\
& \text{subject to} \quad q = p^{-\sigma}P_c^{\sigma-1}E_c, \quad q^x = (p^x)^{-\sigma}P_{c'}^{\sigma-1}E_{c'}, \quad x \in \{0,1\},
\end{aligned}
$$

where E_c is the total expenditure of country c, x is a binary export decision, p^x is the export price, and q^x is the export quantity.

Equilibrium. The government budget is balanced and the total amount of tax revenue is transferred to consumers in lump-sum:

$$
\begin{aligned}
(3.2) \quad T_c = & \int_{\omega\in\Omega_c^L}\left(1-(1-\bar{\tau}^Y(\omega))(1+b(\omega))^\theta\right)\left(p(\omega)q(\omega)+x(\omega)p^x(\omega)q^x(\omega)\right)d\omega \\
& + \int_{\omega\notin\Omega_c^L}\bar{\tau}^Y(\omega)\left(p(\omega)q(\omega)+x(\omega)p^x(\omega)q^x(\omega)\right)d\omega + P_c\int_{\omega\in\Omega^L}\left(b(\omega)+f^b\eta(\omega)\right)d\omega,
\end{aligned}
$$

where Ω_c^L is country c's set of intermediate goods producers participating in lobbying. The first two terms on the right-hand side are the tax revenues from lobbying and non-lobbying firms respectively. The last term is the total lobbying expenditure of lobbying firms.

condition of a firm's maximization problem. The assumption is also empirically supported from the estimate of θ in Section 3.3.3. With the estimate of θ around 0.09-0.11, the assumption is satisfied with the commonly used values for the elasticity of substitution in the literature.

Goods market-clearing implies that

$$P_c Q_c = E_c = w_c L_c + \Pi_c + T_c,$$

where Π_c is the dividend income from households' portfolio. Each household only owns a portfolio of domestic firms, so Π_c is equal to the aggregate profits of domestic firms. Labor market clearing is $L_c = \int_{\omega\in\Omega_c}(l(\omega) + f_c + x(\omega)f_c^x)d\omega$ and balanced trade implies that $\int_{\omega\in\Omega_c^x} p^x(\omega)q^x(\omega)d\omega = \int_{\omega\in\Omega_{c'}^x} p^x(\omega)q^x(\omega)d\omega$.

An equilibrium is formally defined as

Definition III.2. An equilibrium of the economy is defined as (a) a list of wages $\{w_c\}_{c\in\{H,F\}}$, (b) functions $\{p(\omega), p^x(\omega), q(\omega), q^x(\omega), x(\omega), l(\omega), b(\omega), \tau^y(\omega)\}_{\omega\in\Omega_c, c\in\{H,F\}}$, (c) aggregate price indices $\{P_c\}_{c\in\{H,F\}}$, and (d) lump-sum government transfers $\{T_c\}_{c\in\{H,F\}}$ such that (i) a representative household maximizes utility subject to its budget constraint; (ii) firms maximize profits; (iii) the labor market clearing conditions are satisfied; (iv) the goods market clearing conditions are satisfied; (v) the government budgets are balanced; and (vi) trade is balanced in both countries.

Equilibrium Properties. The model nests the two standard models in the literature, Melitz (2003) and Hsieh and Klenow (2009). As $\theta \to 0$ and $Var(1-\bar{\tau}^Y) \to 0$, the model becomes the Melitz model without any firm-specific distortions. If $\theta \to 0$ (or $f^b \to \infty$), in which no firms lobby at all, the model becomes the two-country open economy version of the Hsieh and Klenow (HK) model with exogenous wedges.

I first consider profits conditional on not lobbying. Firms charge constant mark-up $\mu = \sigma/(\sigma-1)$ over their marginal costs and choose to export if profits in the foreign market are sufficiently large to cover the fixed export costs. Profits conditional on not lobbying are expressed as

$$\pi(0;\phi,\bar{\tau}^Y,\eta) = \max_{x\in\{0,1\}}\Big\{\pi^d(0;\phi,\bar{\tau}^Y,\eta) + x\pi^x(0;\phi,\bar{\tau}^Y,\eta)\Big\},$$

where $\pi^d(0;\phi,\bar{\tau}^Y,\eta)$ are profits conditional on not lobbying in the domestic market:

$$\pi^d(0;\phi,\bar{\tau}^Y,\eta) = \underbrace{\frac{1}{\sigma}\left(\mu\frac{w_c}{\phi}\right)^{1-\sigma}(1-\bar{\tau}^Y)^\sigma P_c^{\sigma-1}E_c}_{=\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)} - w_c f_c,$$

and $\pi^x(0;\phi,\bar{\tau}^Y,\eta)$ are profits conditional on not lobbying in the foreign market:

$$\pi^x(0;\phi,\bar{\tau}^Y,\eta) = \underbrace{\frac{1}{\sigma}\left(\mu\frac{\tau_x w_c}{\phi}\right)^{1-\sigma}(1-\bar{\tau}^Y)^\sigma P_{c'}^{\sigma-1}E_{c'}}_{=\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)} - w_c f_c^x.$$

$\tilde{\pi}_c^d(0;\phi,\bar{\tau}^Y,\eta)$ and $\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)$ are the variable profits conditional on not lobbying in domestic and foreign markets.

Once a firm decides to participate in lobbying, the optimal lobbying expenditure is characterized by a firm's first-order condition with respect to b. The optimal lobbying amounts for non-exporters and exporters can be written in terms of variable profits conditional on not lobbying, aggregate variables, and model parameters. The optimal lobbying amounts for non-exporters and exporters, b^{d*} and b^{x*}, are expressed as

$$b^{d*} = C_c^1\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)^{\frac{1}{1-\theta\sigma}} - 1, \qquad C_c^1 = \left(\frac{\theta\sigma}{P_c}\right)^{\frac{1}{1-\theta\sigma}}, \tag{3.3}$$

and

$$b^{x*} = C_c^1\{\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta) + \tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)\}^{\frac{1}{1-\theta\sigma}} - 1. \tag{3.4}$$

Substituting Equation (3.3) into Equation (3.1), profits conditional on lobbying for non-exporters are expressed as

$$\pi^d(b^{d*};\phi,\bar{\tau}^Y,\eta) = C_c^2\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)^{\frac{1}{1-\theta\sigma}} - w_c f_c - P_c[f^b\eta - 1], \tag{3.5}$$

$$C_c^2 = (C_c^1)^{\theta\sigma} - C_c^1$$

and profits conditional on lobbying for exporters are expressed as

(3.6)

$$\pi^x(b^{x*};\phi,\bar{\tau}^Y,\eta) = C_c^2\{\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)+\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)\}^{\frac{1}{1-\theta\sigma}} - w_c f_c - w_c f_c^x - P_c[f^b\eta - 1].$$

The benefits of lobbying are higher revenues due to lower firm-specific distortions. Because lobbying exponentiates the variable profits conditional on not lobbying to the power of $1/(1-\theta\sigma)$, firms with higher ϕ or higher $1-\bar{\tau}^Y$ get larger benefits from lobbying.

Lobbying and export decisions are jointly determined. Because of lobbying, firm export decisions are not independent across markets. With lobbying and export decisions, a firm has four possible options and compares the total profits of each option.[13] A firm's final profit is determined as the maximum of the four options:

$$\begin{aligned}
&\pi(\phi,\bar{\tau}^Y,\eta)\\
&\qquad = \max\Big\{\pi^d(0;\phi,\bar{\tau}^Y,\eta), \pi^d(0;\phi,\bar{\tau}^Y,\eta) + \pi^x(0;\phi,\bar{\tau}^Y,\eta),\\
&\qquad\qquad \pi^d(b^{d*};\phi,\bar{\tau}^Y,\eta), \pi^x(b^{x*};\phi,\bar{\tau}^Y,\eta)\Big\},
\end{aligned}$$

where the terms inside the bracket are non-lobbying non-exporters' profits, non-lobbying exporters' profits, lobbying non-exporters' profits, and lobbying exporters' profits respectively.

With the fixed lobbying costs, lobbying decisions are characterized by a cutoff productivity. The unique cutoff productivity $\bar{\phi}_c^b(\bar{\tau}^Y,\eta)$ is determined by

$$\begin{aligned}
(3.7)\quad \max\Big\{&\pi^d(0;\bar{\phi}_c^b(\bar{\tau}^Y,\eta),\bar{\tau}^Y,\eta), \pi^d(0;\bar{\phi}_c^b(\bar{\tau}^Y,\eta),\bar{\tau}^Y,\eta)\\
&+ \pi^x(0;\bar{\phi}_c^b(\bar{\tau}^Y,\eta),\bar{\tau}^Y,\eta)\Big\}\\
&= \max\Big\{\pi^d(b^{d*};\bar{\phi}_c^b(\bar{\tau}^Y,\eta),\bar{\tau}^Y,\eta), \pi^x(b^{x*};\bar{\phi}_c^b(\bar{\tau}^Y,\eta),\bar{\tau}^Y,\eta)\Big\},
\end{aligned}$$

[13] For example, firms with low productivity (low ϕ) and low fixed lobbying costs (low η) may exist that are not productive enough to be exporters without lobbying, but can be profitable in exporting after lobbying.

where the left-hand side is the maximum profit conditional on not lobbying and the right-hand side is the maximum profit conditional on lobbying. Only firms with productivity above $\bar{\phi}_c^b(\bar{\tau}^Y, \eta)$ participate in lobbying. The cutoff increases in both $\bar{\tau}^Y$ and η.

Similarly, the fixed export costs characterize the unique export cutoff productivity $\bar{\phi}_c^x(\bar{\tau}^Y, \eta)$:

$$\begin{aligned}(3.8) \quad \max\Big\{&\pi^d(0; \bar{\phi}_c^x(\bar{\tau}^Y, \eta), \bar{\tau}^Y, \eta) \\ &+ \pi^x(0; \bar{\phi}_c^x(\bar{\tau}^Y, \eta), \bar{\tau}^Y, \eta), \pi^x(b^{x*}; \bar{\phi}_c^x(\bar{\tau}^Y, \eta), \bar{\tau}^Y, \eta)\Big\} \\ &= \max\Big\{\pi^d(0; \bar{\phi}_c^x(\bar{\tau}^Y, \eta), \bar{\tau}^Y, \eta), \pi^d(b^{d*}; \bar{\phi}_c^x(\bar{\tau}^Y, \eta), \bar{\tau}^Y, \eta)\Big\},\end{aligned}$$

where the left-hand side is the maximum profit conditional on exporting and the right-hand side is the maximum profit conditional on not exporting.

Proposition III.3. *Given Assumption 1,*

(i) A firm's optimal lobbying amounts and profits conditional on lobbying, characterized by Equations (3.3)*,* (3.4)*,* (3.5) *and* (3.6)*, increase in productivity ϕ, decrease in exogenous distortions $\bar{\tau}^Y$ (or increase in $1 - \bar{\tau}^Y$), and increase in market size $P_c^{\sigma-1}E_c + xP_{c'}^{\sigma-1}E_{c'}$;*

and (ii) there exists a unique cutoff productivity of lobbying $\bar{\phi}_c^b(\bar{\tau}^Y, \eta)$, determined by Equation (3.7)*, which increases in exogenous distortions $\bar{\tau}^Y$ (or decreases in $1 - \bar{\tau}^Y$) and increases in stochastic fixed lobbying costs η.*

Proposition III.3 states that higher productivity, lower exogenous distortions, or larger market size are complementary to lobbying. Firms with higher productivity or lower exogenous distortions spend more on lobbying and are more likely to participate in lobbying. In addition, a larger market size increases the firms' overall level of lobbying.

3.2.1 Analytical Results: Aggregate TFP

To develop an intuition for the mechanism behind the possible TFP-improving effect of lobbying, I analytically characterize the effects of lobbying on aggregate TFP in a simpler environment. TFP is defined as the output per worker. To obtain the analytical results, I consider a closed economy in which the fixed lobbying and production costs are zero, so every firm participates in lobbying and production in this environment. The fixed mass of firm M is normalized to be 1. I also assume that $(\phi, 1-\bar{\tau}^Y)$ follows a joint log-normal distribution.

Assumption III.4. *(i) $(\phi, 1-\bar{\tau}^Y)$ follows a joint log-normal distribution, (ii) $f_c = 0$, (iii) $f^b = 0$, (iv) $M = 1$, and (v) $\tau_x = \infty$.*

I compare the three economies. In the first economy, there are no distortions and lobbying is not allowed (Melitz, 2003). In this economy, resources are allocated based on firm productivity, yielding the most efficient outcome. In the second economy, the exogenous distortions are introduced (Hsieh and Klenow, 2009). In this economy, resources are allocated based on both productivity and exogenous distortions. In the third economy, firms can lobby to decrease their output distortions, so overall distortions are endogenously determined by exogenous distortions and firm lobbying decisions. The aggregate TFPs of each economy are derived in the following proposition.

Proposition III.5. *Under Assumptions III.1 and III.4,*

(i) the aggregate TFP of the efficient economy, TFP_{eff}, is

$$\log(TFP_{eff}) = \mathbb{E}[\log\phi] + \frac{(\sigma-1)}{2} Var(\log\phi), \tag{3.9}$$

(ii) the aggregate TFP of the exogenous wedge economy, TFP_{exo}, is

$$\log(TFP_{exo}) = \mathbb{E}[\log\phi] + \frac{(\sigma-1)}{2}Var(\log\phi) - \frac{\sigma}{2}Var(\log(1-\bar{\tau}^Y)), \tag{3.10}$$

and (iii) the aggregate TFP of the lobbying economy, TFP_{endo}, is

$$\begin{aligned} \log(TFP_{endo}) = {} & \mathbb{E}[\log\phi] \\ & + \underbrace{\left(\frac{(\sigma[(1-\theta)^2-1]+1)}{(1-\theta\sigma)^2}\right)}_{\substack{<1 \\ \textit{Concentration effect}}} \times \frac{(\sigma-1)}{2}Var(\log\phi) \\ & - \underbrace{\frac{1}{(1-\theta\sigma)^2}}_{\substack{>1 \\ \textit{Amplification} \\ \textit{effect}}} \times \frac{\sigma}{2}Var(\log(1-\bar{\tau}^Y)) \\ & - \underbrace{\frac{(\sigma-1)\sigma\theta}{(1-\theta\sigma)^2}}_{\substack{>0 \\ \textit{Covariance} \\ \textit{effect}}} \times Cov(\log\phi, \log(1-\bar{\tau}^Y)). \end{aligned} \tag{3.11}$$

The TFP of the efficient economy (Equation (3.9)) increases in the average productivity $\mathbb{E}[log\phi]$ and the variance of productivity $Var(\log\phi)$. The effect of variance of productivity increases in the elasticity of substitution. With a higher variance of productivity, firms with higher productivity are more likely to operate in the economy and provide their goods at a lower price, and as σ becomes larger, the final goods producer is more likely to substitute for a variety at a lower price, increasing the positive effects of the variance of productivity.

When compared to the efficient economy, in the exogenous wedge economy, the variance of the exogenous wedges $Var(\log(1-\bar{\tau}^Y))$ appears as a new term in the TFP (Equation (3.10)). As the dispersion of exogenous wedges becomes larger, resources are more likely to be allocated to firms with low productivity but with high $1-\bar{\tau}^Y$. Therefore, TFP decreases in the variance of the dispersion of the wedge. A higher elasticity of substitution amplifies the negative effect of the variance of the wedges because a final goods producer is more likely to substitute for a lower-priced variety charged by a firm with higher $1-\bar{\tau}^Y$. The covariance between $\log\phi$ and $\log(1-\bar{\tau}^Y)$ does not enter the expression, which is an artifact of the joint log-normality assumption.[14]

When compared to the TFP of the exogenous wedge economy, the three new terms are introduced in the TFP of the lobbying economy (Equation (3.11)), which I label concentration, amplification, and covariance effects. The concentration effect implies that lobbying diminishes the positive effects of the productivity variance. This is because firms with higher productivity lobby more, distorting resource allocation. Similarly, because firms with higher $1-\bar{\tau}^Y$ also lobby more, lobbying amplifies the negative effect of the variance of the exogenous wedges, captured by the amplification effect.

The covariance effect has the most important TFP implications in the second-best world. Depending on the sign of the covariance effect, lobbying can improve TFP over the exogenous wedge economy. If the more productive firms are initially subject to higher exogenous distortions $\bar{\tau}^Y$, which is captured by the negative covariance, they can lobby to decrease the initial distortions. To examine the implications of the covariance effect, I summarize the relationships between the TFPs of the three different economies using the following proposition.

Proposition III.6. *Under Assumptions III.1 and III.4,*

(i) As $\theta \to 0$, $TFP_{endo} \to TFP_{exo}$ *and as* $Var(\log(1-\bar{\tau}^Y)) \to 0$, $TFP_{exo} \to TFP_{eff}$;

[14] Hopenhayn (2014) discusses the impact of the correlation between productivity and distortions on the aggregate TFP. A marginal increase in correlation decreases TFP. However, as the TFP level gets lower, there is overall less demand for labor. This frees up employment, and they are reallocated across all firms in proportion to their marginal product of labor in general equilibrium. Under the joint log-normality assumption, these two effects exactly offset each other.

(ii) $TFP_{eff} \geq TFP_{endo}$ *and* $TFP_{eff} \geq TFP_{exo}$*;*

and (iii) lobbying can increase TFP, that is, $TFP_{exo} < TFP_{endo}$ *under certain conditions. The necessary condition is* $Cov(\log\phi, \log(1-\bar{\tau}^Y)) < 0$*.*

Lobbying always decreases TFP when compared to the efficient economy (Proposition III.6(ii)). However, TFP can increase over the exogenous wedge economy under certain conditions through the covariance effect (Proposition III.6(iii)). The necessary condition is $Cov(\log\phi, \log(1-\bar{\tau}^Y)) < 0$, the condition under which the more productive firms are subject to a higher pre-lobbying exogenous distortion. With negative covariance, the more productive firms can overcome a higher pre-lobbying distortion through lobbying, which can increases aggregate TFP. However, if the covariance effect takes positive values because lobbying allocates resources excessively toward large lobbying firms, lobbying always amplifies the initial level of resource misallocation. Since the net effect depends on the sign and magnitude of $Cov(\log\phi, \log(1-\bar{\tau}^Y))$, the measurement of this covariance will be the key to the quantification below.

Trade can affect aggregate TFP through lobbying, although the direction is ambiguous. Suppose the more productive firms are subject to higher pre-lobbying distortions, and there is a decrease in trade costs. An increase in market size induced by trade can increase TFP through the covariance effect by inducing more productive exporters to lobby more. However, other directions are also possible. Because only exporters are better off from increased market size, lobbying expenses can be more unequally concentrated among a few big exporters, making the concentration and amplification effects dominate the covariance effect. Section 3.4 considers the impact of globalization on lobbying and TFP in detail.

3.3 Quantification

This section quantitatively assesses the impact of lobbying. I discuss how $Cov(\log\phi, \log(1-\bar{\tau}^Y))$, the key condition for the welfare implications of lobbying, can be identified from the observable moments in the data. Using an instrumental variable (IV) strategy based on the institutional details of US political system, I structurally estimate θ, which governs the elasticity of output taxes with respect to lobbying expenditure. The remaining parameters are calibrated to the firm-level data and other data sources using the method of moments, allowing for heterogeneity in productivity, exogenous wedges, and fixed lobbying costs.[15] I then evaluate the TFP and welfare implications of lobbying under different scenarios.

3.3.1 Data

I combine firm balance sheet data with lobbying, trade, and sector-level databases. I match firm-level balance sheet data to the lobbying database based on firm name, and then the firm-level data are matched to the trade and sector-level data according to firm industry affiliation.

Lobbying and Firm-Level Data. I construct the main firm-level database by merging the lobbying data obtained from the Center for Responsive Politics (CRP) with Compustat, which covers public firms listed on the North American stock markets. The sample period is from 1998 to 2015. The lobbying data became publicly disclosed since 1998 after the Lobbying Disclosure Act (LDA) (1995). LDA requires active registered lobbyists to file activity reports each quarter. Each report contains

[15] I choose the model with a fixed mass of firms as the baseline for two reasons. First, Compustat only covers big firms in the US. The free entry assumption is inconsistent with this feature of the data. Second, although the entry effect of lobbying is also an interesting issue, the main focus of this paper is the effect of lobbying given the firm-specific exogenous distortions across firms. I also show that my quantitative results are robust under the free entry assumption, which is reported in Panel B of Table 3.5.

Table 3.1: Descriptive Statistics

Sales ($1M)	Lobbying Amounts ($1K)	$1[Lobby_{it} > 0]$	$1[Lobby_{it} > 0] \neq 1[Lobby_{i,t-1} > 0]$
(1)	(2)	(3)	(4)
1980.4	188.1	0.137	0.080
(11055.7)	(1387.5)	(0.344)	(0.271)

Notes. This table provides descriptive statistics of the main data set. There are 39,692 firm-year level observations with unique 4989 firms. Standard deviations are reported in parentheses. The sample period is 1998-2015.

various information on firm lobbying practices, such as lobbying expenditures, issue areas, and a brief description of lobbying activities. I restrict my sample to the manufacturing sectors.

Descriptive statistics of the raw data are presented in Table 3.1. Columns (1) and (2) report the average sales and average lobbying expenditures. In column (3), about 13% of firm-year level observations have spent positive amounts on lobbying. Column (4) reports the percentage of extensive margin changes. Only about 8% of the total observations changed the lobbying status during the sample period, indicating that lobbying status is persistent.[16]

Industry and Trade Data. Bilateral trade data are extracted from the UN Comtrade at the 6-digit HS product level. I convert 6-digit HS codes into 4-digit SIC codes using Pierce and Schott's (2012) concordance. Following Autor et al. (2013), I aggregate at a slightly higher level so that each industry code is matched with at least one six-digit HS code. Industry data comes from the NBER-CES Manufacturing Industry Database for 1971-2009. The industry and trade data are matched with the firm-level data using firm SIC 4-digit codes and headquartered states. For some firms that report only 2-digit or 3-digit SIC codes, I take the average across 4-digit SIC

[16]This number is consistent with Kerr et al. (2014) who also report that about 92% of firms lobby in a given year also participate in lobbying in the next year.

codes and then match at the aggregated level.

3.3.2 Identification of $\mathbf{Cov}(\log\boldsymbol{\phi}, \log(\mathbf{1} - \bar{\boldsymbol{\tau}}^{\boldsymbol{Y}}))$

The direction of the impact of lobbying on aggregate TFP depends on $Cov(\log\phi_{it}, \log(1-\bar{\tau}^Y_{it}))$, where subscripts i and t denote for firm and period.[17] Although ϕ_{it} and $1-\bar{\tau}^Y_{it}$ are not directly observable in the data, I show that the covariance between log of the optimal lobbying expenditure b^*_{it} and log of exogenous wedges $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ is the identifying moment for $Cov(\log\phi_{it}, \log(1-\bar{\tau}^Y_{it}))$ and $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ can be computed from the data (Nakamura and Steinsson, 2018).

I first describe how to back out $\log(1-\bar{\tau}^Y_{it})$ from the data and then how to compute $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$. Following Hsieh and Klenow (2009), overall firm output wedges inclusive of both exogenous and endogenous wedges are identified from the measured revenue total factor productivity (TFPR)[18]:

$$TFPR_{it} = \frac{1}{MRPL_{it}} = \underbrace{\left(\frac{\text{Value-Added}_{it}}{\text{Employment}_{it}}\right)^{-1}}_{\text{Data}} \propto \underbrace{(1+b^*_{it})^{\theta}}_{\text{Data}} \times \underbrace{(1-\bar{\tau}^Y_{it})}_{\text{Unobservable}}.$$

Given the estimate of θ and the data on the lobbying amounts b^*_{it}, after dividing the TFPR by $(1+b^*_{it})^{\theta}$, I can separately identify the endogenous wedges $(1+b^*_{it})^{\theta}$ and the exogenous wedges $1-\bar{\tau}^Y_{it}$ from the measured TFPR. Then, after measuring $(1+b^*_{it})^{\theta}$ and $1-\bar{\tau}^Y_{it}$ from the data in the previous step, the empirical moment of the following object can be computed:

$$Cov(\underbrace{\log(1+b^*_{it})}_{\text{Data}}, \underbrace{\log(1-\bar{\tau}^Y_{it})}_{\substack{\text{From the}\\\text{previous step}}}),$$

[17] The model presented in the previous section is static, whereas I observe multiple periods in the data. I interpret the observations in the data as the repeated sequence of the static model.

[18] If there were no firm-specific output wedges, the inverse of MRPL does not vary across firms within industry, because all firms are equalizing its MRPL to a common wage. Any within industry variations in the inverse of MRPL are attributable to firm-specific output wedges and these variations can be used to infer firm-specific output wedges. TFPR is equivalent to the inverse of MRPL when labor is the only factor of production.

which is the identifying moment of $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$.

How can $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ be the identifying moment for $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$? The optimal lobbying amounts b^*_{it} increase in both ϕ_{it} and $1-\bar{\tau}^Y_{it}$. To infer $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$, I use these monotonic relationships and $1-\bar{\tau}^Y_{it}$ backed out from the data. Holding ϕ_{it} constant, firms with higher $1-\bar{\tau}^Y_{it}$ (or lower $\bar{\tau}^Y_{it}$) spend larger lobbying amounts, so $\log(1+b^*_{it})$ and $\log(1-\bar{\tau}^Y_{it})$ are positively correlated. However, as $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$ becomes more negative, because firms with higher ϕ_{it} also lobby more, this positive relationship between $\log(1+b^*_{it})$ and $1-\bar{\tau}^Y_{it}$ is weakened. For the sufficiently negative values of $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$, which is the necessary condition of the TFP-improving effects, $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ can take negative values. In fact, the more negative $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$ is, the more negative $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ becomes. From this monotonic relationship, I can infer the sign and magnitude of $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$. The following proposition summarizes this.

Proposition III.7. ***(Identifying Moment)*** *Under Assumptions III.1 and III.4(i, iii),*

(i) when $f^b = 0$ *and in a closed economy,*

(a) $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ *is expressed as*

$$\underbrace{Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))}_{>0 \text{ or } <0, \text{Observable}} = \underbrace{\frac{\sigma-1}{1-\theta\sigma}}_{>0} \times \underbrace{Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))}_{\substack{>0, \text{ or } <0, \\ \text{Unbservable}}} + \underbrace{\frac{\sigma}{1-\theta\sigma} \times Var(\log(1-\bar{\tau}^Y_{it}))}_{\substack{>0, \\ \text{Observable}}},$$

(b) there is a one-to-one mapping between $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$ *and* $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it}))$*,*

(c) $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it})) < 0$ *only if* $Cov(\log \phi_{it}, \log(1-\bar{\tau}^Y_{it})) < 0$.

and (ii) *when* $f^b > 0$ *and in an open economy,*

$$\underbrace{Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y)|b_{it}^*>0)}_{Observable} = \sum_{x_{it}'\in\{0,1\}} \mathbb{P}[\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), x_{it}^* = x_{it}']$$
$$\times \left\{ \frac{\sigma-1}{1-\theta\sigma} Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y)|\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), x_{it}^* = x_{it}') \right.$$
$$\left. + \frac{\sigma}{1-\theta\sigma} Var(\log(1-\bar{\tau}_{it}^Y)|\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), x_{it}^* = x_{it}') \right\},$$

where x_{it}^* *is a firm's optimal export decision.*[19]

Proposition III.7(i) states that in a closed economy in which $f^b = 0$ so that every firm is lobbying, there is a one-to-one mapping between $Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y))$ and $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$ and $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$ can be directly inferred from the observables. Given the estimate of θ, the value of the elasticity of substitution σ, and the measured $1-\bar{\tau}_{it}^Y$, I can compute the empirical moment of $\sigma/(1-\theta\sigma)Var(\log(1-\bar{\tau}_{it}^Y))$. By subtracting this empirical moment from $Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y))$, I can recover $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$. Moreover, $Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y))$ takes negative values only when the necessary condition of the TFP-improving effects is satisfied, that is, when $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$ is negative. Therefore, if $Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y))$ computed from the data takes negative values, I can indirectly infer that the more productive firms are initially more taxed.

In an open economy with positive fixed lobbying and export costs, Proposition III.7(ii) states that although $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$ cannot be directly computed without further information on other aggregate endogenous variables and fixed lobbying costs, $Cov(\log(1+b_{it}^*), \log(1-\bar{\tau}_{it}^Y)|b_{it}^*>0)$ is informative on $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y))$ through its information on the conditional covariance $Cov(\log\phi_{it}, \log(1-\bar{\tau}_{it}^Y)$

[19]Note that $\{\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), x_{it}^* = 1\}$ and $\{\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), x_{it}^* = 0\}$ are equivalent to $\{\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), \phi_{it} \geq \bar{\phi}_c^x(\bar{\tau}_{it}^Y, \eta_{it})\}$ and $\{\phi_{it} \geq \bar{\phi}_c^b(\bar{\tau}_{it}^Y, \eta_{it}), \phi_{it} \leq \bar{\phi}_c^x(\bar{\tau}_{it}^Y, \eta_{it})\}$.

—$\phi_{it} \geq \bar{\phi}^b_c(\bar{\tau}^Y_{it}, \eta_{it}), x^*_{it} = x'_{it})$, where x^*_{it} is an optimal export decision and $x'_{it} \in \{0, 1\}$ is an export status. $Cov(\log(1 + b^*_{it}), \log(1 - \bar{\tau}^Y_{it})|b^*_{it} > 0)$ can be computed using the samples with positive lobbying amounts.

3.3.3 Estimation of θ

I assume that output wedges take the following form: for firm i in sector j at time t,

$$1 - \tau^Y_{it} = exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \delta_i + \delta_{jt}) \times (1 - \bar{\tau}^Y_{it})(1 + b^*_{it})^{\theta},$$

where $\mathbf{X}_{it}$ are observable characteristics, and δ_i and δ_{jt} are firm and sector-time fixed effects, respectively. The inverse of the marginal revenue of product of labor (MRPL) is proportional to the output wedge:

$$\frac{1}{MRPL_{it}} = \frac{w_t L_{it}}{\text{Value Added}_{it}} \propto \left(exp(\mathbf{X}'_{it}\boldsymbol{\beta} + \delta_i + \delta_{jt}) \times (1 - \bar{\tau}^Y_{it})(1 + b^*_{it})^{\theta} \right), \tag{3.12}$$

where MRPL is measured as value-added divided by wage bills.[20]

I introduce an additional dimension of heterogeneity in the variable costs of lobbying. I assume that to spend lobbying amount of b_{it}, a firm has to pay $Z_{it}b_{it}$ amount of variable costs, where Z_{it} is a firm-specific observable cost shifter. I use Z_{it} as an instrumental variable to consistently estimate θ, dealing with the endogeneity problem which is discussed later in the paper. This allows firms to have different levels of variable costs, depending on Z_{it}.[21] With the additional heterogeneity in the variable costs of lobbying, the optimal lobbying expenditure b^*_{it} also depends on Z_{it}. Taking the log on both sides of Equation (3.12), I can derive the following estimable

[20] Value-added is calculated as sales multiplied with sectoral value-added shares and the wage bills are calculated as employment multiplied with sector-state specific wage rate. Sectoral value-added shares are calculated from NBER-CES Manufacturing database. The wage rate is obtained from the US Census County Business Pattern data. If labor markets are segmented, firms may face different wages depending on their industry affiliations and location. In such a case, the regression results may be driven by variation in wages rather than variations in output wedges. Dividing value-added by wage bill mitigates this concern.

[21] In the model described in Section 3.2, all firms have the same level of variable costs of lobbying, that is, $Z_{it} = 1$, $\forall i$. With additional heterogeneity of Z_{it}, the total lobbying cost of firm i is $P_t(Z_{it}b^*_{it} + f^b\eta_{it})$.

regression model: [22]

$$\text{(3.13)}\quad \log 1/MRPL_{i,t+1} = \theta \log(1+b^*_{it}) + \mathbf{X}'_{it}\boldsymbol{\beta} + \delta_i + \delta_{jt} + \log(1-\bar{\tau}^Y_{it}),$$

$$\text{where} \qquad b^*_{it} = b^*(\phi_{it}, \bar{\tau}^Y_{it}, \eta_{it}, Z_{it}).$$

Because $\log(1-\bar{\tau}^Y_{it})$ appears as the structural error term in Equation (3.13), the OLS estimates suffer from the endogeneity problem. Because lobbying is a function of $1-\bar{\tau}^Y_{it}$, $\log(1+b^*_{it})$ is correlated with the error term. In addition, a potential correlation between ϕ_{it} and $1-\bar{\tau}^Y_{it}$ can cause $\log(1+b^*_{it})$ to be correlated with the error term. Because the correlation between ϕ_{it} and $1-\bar{\tau}^Y_{it}$ has important TFP implications in the model, assuming independence between ϕ_{it} and $1-\bar{\tau}^Y_{it}$ leads to both omitted variable bias econometrically and misleading TFP implications theoretically.

Instrumental Variable Strategy

I instrument for lobbying using the state-level time-varying appointment of a Congress member as chairperson of the Appropriations Committees of the Senate or House of Representative (Aghion et al., 2009; Cohen et al., 2011). The data on membership on all congressional committees are obtained from Stewart and Woon (2017).

Institutional Setting. A local Congress member's appointment as a chairperson of the Appropriations Committees works as an exogenous cost-shifter of lobbying. The Appropriations Committees are in charge of discretionary spending, giving the Appropriations Committees larger power than any other congressional committees and making them more prone to be lobbied.[23] With budget responsibilities, the

[22] b^*_{it} is in the units of final goods in the model but the data only reports the total lobbying expenditure $P_t b^*_{it}$. To map the model to the data, I assume that at the equilibrium, P_t is normalized to 1, implying that the lobbying expenditures reported in the data can be interpreted in terms of the units of final goods.

[23] See Stewart and Groseclose (1999), Blanes i Vidal et al. (2012), and Berry and Fowler (2018).

chairperson of the Appropriations Committees has greater power than any other members and often allocates more federal spending to the state that the chairperson represents.[24] With an increase in potential grants and federal contracts opportunities through discretionary spending, local Congress members who are chairpersons in the Appropriations Committees can increase the efficiency of lobbying of local firms in the same state as local Congress members. Because the nomination of the chairperson of congressional committees is determined by seniority and a complicated political process, the nomination of the chairperson of the Appropriations Committees is exogenous to the economic conditions of individual states or firms.[25]

IV Regression Results. I estimate Equation (3.13) in first differences with IV. The samples were averaged over six years.[26] The IV is the average of a dummy variable that equals one if a state Congress member is a chairperson in the Appropriations Committees in either Senate or House for six years. To control for the state-common effects of the nomination of chairpersonship, I control detailed state-level tax incentives and transfers from the federal government.[27] Columns (1)-(3) of Table 3.2 report the regression results. In column (3), dummies indicating quantiles of firm sales at the beginning of the period are controlled, allowing for possible heterogeneous trends in output wedges depending on firm size. Once the endogeneity problem is corrected using IV, I obtain significantly positive coefficients with strong first-stage results.[28] A 1% increase in lobbying was associated with a 0.09-0.1% increase in output wedges.

[24] For example see Berry and Fowler (2016) finds that the chairs or the important positions of the Appropriations Committees bring more earmarks to the states they represent. Aghion et al. (2009) and Cohen et al. (2011) find that local earmarks or federal expenditures on education increase once local Congress members become the chair of the important committees in Congress.

[25] A change of chairpersonship is associated with the unexpected loss of reelection, retirement, or death of the current chair (Aghion et al., 2009; Cohen et al., 2011).

[26] This mitigates the potential seasonality of lobbying expenditures caused by political cycles and measurement errors of MRPL.

[27] State-level tax incentives are obtained from Bartik (2018). Specifically, I control corporate income taxes, job creation tax credits, investment tax credits, R&D tax credits, property tax abatement. The transfers from the federal government are obtained from the US Census.

[28] The first stage results are reported in Online Appendix Table C.7.

Table 3.2: Estimating θ

Dep.	$\log(1/MRPL)$			$\log(1-ETR)$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+b^*_{it})$	-0.004	0.092***	0.101**	-0.003	0.076**	0.077**
	(0.005)	(0.032)	(0.039)	(0.003)	(0.029)	(0.032)
KP-F	.	31.81	29.84	.	31.81	29.84
Industry FE	Y	Y	Y	Y	Y	Y
State Control	Y	Y	Y	Y	Y	Y
Firm Control	N	N	Y	N	N	Y
N	1216	1216	1216	1216	1216	1216

Notes. This table reports OLS and IV estimates of Equation (3.13). The dependent variable is the log of the inverse of MRPL in columns (1)-(3), and the dependent variable is $\log(1-ETR)$ in columns (4)-(6). ETR is defined in Equation (3.14). The OLS estimates are reported in columns (1) and (4). The IV estimates are reported in columns (2), (3), (5), and (6). The IV is the average of a dummy variable equals one if a Congress member of the state where a firm is headquartered becomes a chair of the Appropriations Committees in the House or Senate over six years. State control includes corporate income tax, job creation tax credit, investment tax credit, R&D tax credit, property tax abatement, and transfers from the federal government. Firm control includes dummies indicating quantiles of a firm's initial sales. KP-F is Kleibergen-Paap F-statistics. The samples are averaged over six years. Standard errors are clustered at the state level. * p<0.1; ** p<0.05; *** p<0.01.

The direction of bias in the OLS estimate can be interpreted through the lens of the model. When comparing the OLS and IV estimates in Table 3.2, the OLS estimate is downward-biased. The direction of bias has implications for the underlying correlation between productivity and exogenous wedges. Holding ϕ_{it} and η_{it} constant, $\log(1+b^*_{it})$ is positively correlated with the error term $\log(1-\bar{\tau}^Y_{it})$, making the estimated coefficient be biased upward. However, when $Cov(\log\phi_{it}, \log(1-\bar{\tau}^Y_{it}))$ is sufficiently negative, which is the necessary condition for lobbying to improve TFP, $\log(1+b^*_{it})$ can be negatively correlated with the error term, giving the OLS estimate a downward bias. I show that this is indeed the case in Section 3.3.5.

Additional Robustness Checks. I extend the model to include two production factors: labor and capital.[29] Lobbying has a statistically significant relationship with

[29]See Online Appendix Section C.4.2 for more detail.

MRPL but not with marginal revenue product of capital (MRPK). These results are reported in Online Appendix Table C.5. I also conduct an event study to check whether the appointment of the chairperson has pre-trends in lobbying expenditures.[30] The pre-trends can detect potential spurious correlations arising from pre-existing confounding factors or reverse causality problems. These pre-trends are reported in Online Appendix Figure C.4. I find no pre-trends in the appointment, supporting the exclusion restriction of the IV.

External Validity. If the model is misspecified, it is problematic to infer the MRPL as a firm-specific wedge.[31] To examine whether the findings are robust to model misspecification, I use the cash effective tax rate (ETR) developed by Dyreng et al. (2008, 2017) as an alternative proxy for a firm-specific wedge.[32] The ETR captures a firm's long-run tax avoidance activities, such as tax and investment credits. The ETR is constructed directly from the data rather than relying on the model structure. The ETR is defined as

$$ETR_{it} = \frac{\sum_{h=1}^{6} TXPD_{it-h}}{\sum_{h=1}^{6}(PI_{it-h} - SPI_{it-h})}, \tag{3.14}$$

where $TXPD_{it}$, PI_{it} and SPI_{it} are the cash taxes paid, the pre-tax income and the special items, averaged over six years.[33] I use $\log(1 - ETR_{it})$ as the alternative dependent variable, consistent with the output wedges measured by the inverse of the MRPL.[34] Columns (4)-(6) of Table 3.2 report the regression results. The estimated coefficients are qualitatively and quantitatively similar to $\log(1/MRPL_{it})$.[35]

[30] See Online Appendix Section C.4.1 for more detail.

[31] For example, although there is no firm-specific exogenous wedge, Asker et al. (2014) and David and Venkateswaran (2019) show that frictions of input adjustment can result in the dispersion of MRPL and MRPK.

[32] Arayavechkit et al. (2017) similarly use this measure and shows that this measure is correlated with MRPK.

[33] Special items represent unusual or nonrecurring items presented above taxes by the company. Following Hanlon and Slemrod (2009), I reset ETR to zero for a minimum and 0.5 for a maximum to mitigate the effect of outliers.

[34] The ETR is interpreted as firm-specific taxes, so $1 - ETR$ can be mapped to the output wedges in the model.

[35] The results are robust to different transformation of ETR and different winsorization schemes. The results are reported in Online Appendix Table C.6

3.3.4 Calibration

The two countries Home and Foreign are calibrated to the data corresponding to the US and the rest of the world. I assume that $(\log\phi, \log(1-\bar{\tau}^Y))$ of the US follows a joint log-normal distribution:

$$\begin{pmatrix} \log\phi \\ \log(1-\bar{\tau}^Y) \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{US} \\ 0 \end{pmatrix}\begin{pmatrix} \sigma_\phi & \rho \\ \rho & \sigma_{\bar{\tau}^Y} \end{pmatrix}\right),$$

where the mean of $1-\bar{\tau}^Y$ is normalized to zero. σ_ϕ and $\sigma_{\bar{\tau}^Y}$ are standard deviation of $\log\phi$ and $\log(1-\bar{\tau}^Y)$, and ρ is the correlation between $\log\phi$ and $\log(1-\bar{\tau}^Y)$. I assume that η is independent of ϕ and $1-\bar{\tau}^Y$. η is also log-normally distributed with a mean of zero and a standard deviation of σ_η.[36] Given the absence of micro-level data on Foreign and that Foreign affects the US only through the aggregate variables, I assume that foreign firms cannot lobby and Foreign has no distortions, and I take σ_ϕ^F, f, and f_x of Foreign to be the same as those of the US.

$\{\theta, \sigma, L^{US}, L^F, \mu_{US}, \mu_F, \tau_x, M_e^{US}\}$ are calibrated externally. I set θ to 0.09, which is the baseline estimate in Table 3.2. The relative labor of Foreign to US L^F/L^{US} is set to be 7.2 to match the relative labor force from the Penn World Table (PWT) (Feenstra et al., 2015).[37] The relative mean of the US productivity to Foreign productivity μ_{US}/μ_F is calibrated to be 3.5 to match the relative GDP per capita from the PWT. I set the elasticity of substitution to be 3 following Hsieh and Klenow (2009). I set the symmetric iceberg trade costs τ_x to be 1.7 following Anderson and Van Wincoop (2004). The exogenous firm mass of the US M_e^{US} is normalized to 1.

The remaining parameters $\Theta = \{\sigma_\phi, \sigma_{\bar{\tau}^Y}, f^b, \sigma_\eta, \rho, f_x^{US}, M_e^F, f_x^F\}$ are calibrated jointly using the method of moments to match the model moments with the 1999 data

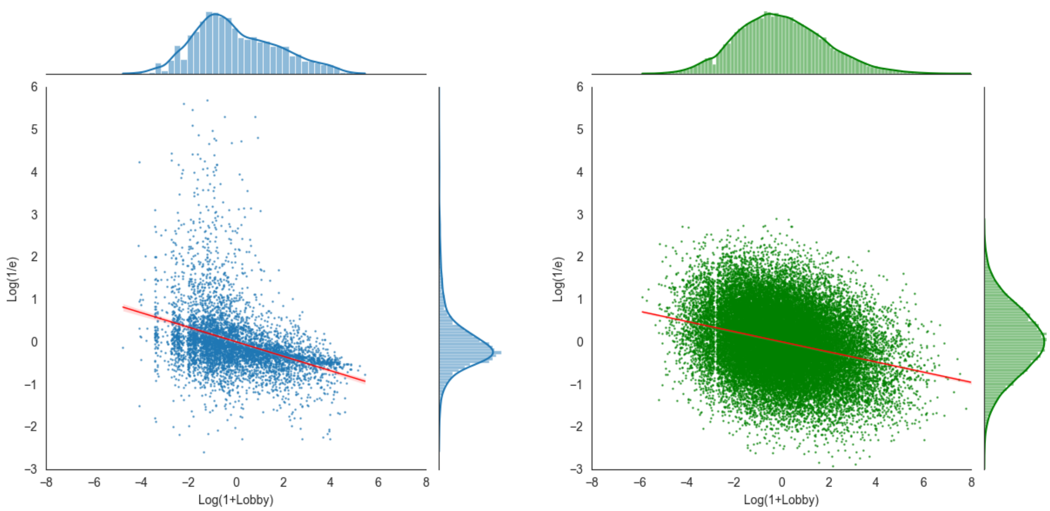
[36] The mean of η is not separately identifiable with f^b.

[37] To construct labor and aggregate productivity level of Foreign, I choose the top 15 trading partners in 2006: Canada, Mexico, China, Japan, Germany, United Kingdom, South Korea, Taiwan, France, Malaysia, Italy, Netherlands, Venezuela, Brazil, and Ireland. Then, I aggregate up import, export, GDP, and labor of these countries.

Table 3.3: Model Parameters

Parameter		Value	Identifying Moment
Externally calibrated			
σ	Elasticity of substitution	3	Hsieh and Klenow (2009)
L_F/L_{US}	Foreign & US Labor	7.2	Relative labor of Foreign to the US (PWT)
μ_{US}/μ_F	Foreign & US productivity	3.5	Relative GDP per capita (PWT)
τ_x	Iceberg trade cost	1.7	Anderson and Van Wincoop (2004)
θ	Lobbying parameter of output wedge	0.09	Own estimate
Internally estimated			
σ_ϕ	Std. productivity	1.9	Std. of log(Sale), Sales dist.
$\sigma_{\bar{\tau}^Y}$	Std. output wedge	0.83	Std. of $1/MRPL$
f^b	Fixed cost of lobybing	7.2	Lobbying expenditures & sales dist.
σ_η	Std. fixed lobbying cost	2.80	Lobbying expenditures & sales dist.
ρ	Corr(output wedge, productivity)	-0.87	$Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)\|b^*>0)$
f_x	Fixed export	0.04	Fraction of firms exporting (Bernard et al., 2007)
f	Fixed cost of production	1e-6	Sales dist.
M_e^{US}	Mass of firms (US)	1	Normalization
M_e^F	Mass of firms (Foreign)	1.3e-5	US export share (PWT)

Notes. This table summarizes the calibrated values for the parameters of the model and their identifying moments.



Panel A. Data, $\beta = -0.36$ Panel B. Model Fit, $\beta = -0.34$

Figure 3.1: The Identifying Moment. $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it})|b^*_{it} > 0)$. Data and Model Fit

Notes. X and Y-axis represent $\log(1+b^*_{it})$ and $\log(1-\bar{\tau}^Y_{it})$ backed out from the 1999 data. $\log(1-\bar{\tau}^Y_{it})$ is normalized by the mean of TFPR across firms weighted by value-added within industry. Each dot in Panels A and B is firm-year observation with positive lobbying amounts from the actual and the model-generated data. The red line represents linear fit with 99% confidence interval. The slope coefficients β are reported at the bottom. $\log(1+b^*_{it})$ and $\log(1-\bar{\tau}^Y_{it})$ are demeaned in both figures. The distributions at the top and the right are histograms and their associated kernel density estimates of $\log(1+b^*_{it})$ and $\log(1-\bar{\tau}^Y_{it})$.

Table 3.4: Data and Model Moments

Target Moments	Data (1999)	Moment
Share of lobbying firms (sales above p90)	0.47	0.47
Share of lobbying firms (sales between p90 and p75)	0.09	0.09
Std. of log sales	2.48	2.60
Mean (sale $\geq$ p75) - Mean (P75 $\geq$ sale $>$ p50)	2.14	2.58
Mean (p75 $\geq$ sale $>$ p50) - Mean (P50 $\geq$ sale $>$ p25)	1.60	1.63
Mean (p50 $\geq$ sale $>$ p25) - Mean (P25 $\geq$ sale $>$ p10)	1.56	1.56
Mean (p25 $\geq$ sale $>$ p10) - Mean (p10 $>$ sale)	2.35	2.00
Std of TFPR (1/MRPL)	0.86	0.81
Cov. $\log(1+b)$ and $\log(1-\bar{\tau}^Y)$	-0.38	-0.39
Share of exporters	0.18	0.19
Export share of GDP	0.10	0.10

Notes. All the moments except for share of exporters and export share of GDP are calculated from Compustat and the lobbying database. Share of exporters is from Bernard et al. (2007). Export share of GDP is from the PWT.

counterparts.[38] I choose the moments that are relevant and informative about the underlying parameters. I fit ρ to match $Cov(\log(1+b^*_{it}), \log(1-\bar{\tau}^Y_{it}))$, the identifying moment in Proposition III.7. The standard deviation of productivity σ_ϕ is set to match the sales distribution of Compustat. Five bins were constructed based on the four percentiles: 75th (p75), 50th (p50), 25th (p25), and 10th (p10). I fit the overall standard deviation of sales and the mean of the log sales of each bin. I fit $\sigma_{\bar{\tau}^Y}$ to the standard deviation of $1/MRPL_{it}$. Because $1/MRPL_{it} = (1-\bar{\tau}^Y_{it})(1+b^*_{it})^\theta$, conditional on observable b and the value of parameter θ, $\sigma_{\bar{\tau}^Y}$ can be identified from the standard deviation of $1/MRPL$. The fixed lobbying costs f^b and standard deviation σ_η are calibrated to match the share of lobbying firms in the different sales bins. f^b is identified by the overall share of lobbying firms. σ_η is identified by

[38] More precisely, the parameters minimize the following objective function:

$$\hat{\Theta} = argmin_\Theta\{(\mathbf{m}-\mathbf{m}(\Theta))'\mathbf{W}(\mathbf{m}-\mathbf{m}(\Theta))\}, \qquad \text{subject to} \quad L(\Theta) = 0,$$

where $\mathbf{m}$ and $\mathbf{m}(\Theta)$ are empirical and model moments, W is the weighting matrix, and $L(\Theta) = 0$ is the set of constraints imposed by the equilibrium conditions. Following Su and Judd (2012), I solve the constrained minimization problem that minimizes the distance between empirical and model moments subject to the constraints imposed by a set of equilibrium conditions described in the previous section. I set W to be the identity matrix. The moments are normalized to convert the difference between the model and the empirical moments into the percentage deviation. The solution to the problem is not guaranteed to be the global minimum. Therefore, I solve the constrained minimization problem multiple times with different starting points to deal with the local minimum problem. The equilibrium conditions are described in more detail in Online Appendix Section C.5.1.

the fraction of medium-sized firms that are lobbying. In the model, the pattern of many medium-sized firms lobbying relative to their sales is rationalized by the high variance of η. Without this high variance of η, sales become highly correlated with lobbying expenditures and the model cannot predict medium-sized firms' lobbying. I fit the fixed costs of production using the difference between the mean of log sales of firms with sales between p25 and p50 and the mean of log sales of firms with sales below p10. Because the fixed costs of production only affect the production decisions of small-sized firms, this moment can pin down the parameter.

Model Fit. Table 3.3 reports internally estimated and externally chosen parameters. Table 3.4 reports the model fit. The data moments are well-approximated in the model. Figure 3.1 graphically illustrates the identifying moment observed in the data. Panel A plots $\log(1+b^*_{it})$ and $\log(1-\bar{\tau}^Y_{it})$ for firm-year level observations with positive lobbying amounts. The negative relationship implies that $\log \phi_{it}$ and $\log(1-\bar{\tau}^Y_{it})$ are likely to be negatively correlated in the underlying distribution. In Panel B of Figure 3.1, using the model-generated data, I plot the same figure with Panel A. The model reproduces the identifying moment observed in the data.

3.3.5 Quantitative Results

Decomposition of the measured TFPR. The observed TFPR dispersion is commonly used to measure the extent of misallocation in an economy.[39] At an efficient equilibrium, firms equate their TFPR to the common wage, and therefore there should be no TFPR dispersion within industry. With output wedges, however, firms do not always equate their TFPR to the common wage, resulting in TFPR dispersion.

[39] The dispersion of TFPR is equivalent to aggregate TFP under the assumptions presented in Hsieh and Klenow (2009). These assumptions include the Cobb-Douglas production function, CES demand structure with monopolistic competition, exogenous firm mass, and closed economy. If these assumptions are violated, the dispersion is not directly mapped to the aggregate TFP and becomes a reduced form measure for the aggregate TFP.

The observed TFPR dispersion can be decomposed as

$$(3.15)\quad Var\left(\log\frac{TFPR_{it}}{TFPR_{jt}}\right) = Var\left(\log\frac{1/MRPL_{it}}{TFPR_{jt}}\right) = Var(\log(\widetilde{1-\bar{\tau}^Y_{it}})(1+b^*_{it})^\theta)$$

$$= \underbrace{Var(\log(\widetilde{1-\bar{\tau}^Y_{it}}))}_{\substack{\textit{HK dispersion}\\ \geq 0}} + \underbrace{\theta^2 Var(\log(1+b^*_{it}))}_{\substack{\textit{Lobbying dispersion}\\ \geq 0}} + \underbrace{2\theta Cov(\log(1+b^*_{it}), \log(\widetilde{1-\bar{\tau}^Y_{it}}))}_{\substack{\textit{Covariance dispersion}\\ \geq 0 \text{ or } <0}},$$

$$\widetilde{1-\bar{\tau}^Y_{it}} = (1-\bar{\tau}^Y_{it})/TFPR_{jt},$$

where $\widetilde{1-\bar{\tau}^Y_{it}}$ is an exogenous wedge backed out from the data, normalized by the industry-level TFPR ($TFPR_{jt}$). The industry-level TFPR is obtained as the mean of TFPR across firms weighted by value-added within industry. The normalization differences out any sector-level distortions that are common across firms, which makes firms across different sectors comparable.

The observed overall dispersion can be decomposed into three components: (1) HK, (2) lobbying, and (3) covariance dispersion. The HK dispersion is induced by exogenous wedges (Hsieh and Klenow, 2009). If $\log(1-\bar{\tau}^Y_{it}) = 0$ for all firms, the HK dispersion becomes zero. Without lobbying, this was the only source of dispersion. The question is whether lobbying mitigates or amplifies this pre-lobbying HK dispersion. Lobbying introduces two additional sources: lobbying and covariance dispersion. The lobbying dispersion is always positive, so the lobbying dispersion always amplifies the HK dispersion and increases the overall dispersion. Whether lobbying can mitigate the HK dispersion depends on the covariance dispersion. The covariance dispersion can take either negative or positive values. If the covariance dispersion is sufficiently negative, it can offset the lobbying dispersion and make the overall observed dispersion even smaller than the HK dispersion. However, if the covariance dispersion is positive, lobbying makes the overall dispersion larger than the HK dispersion.

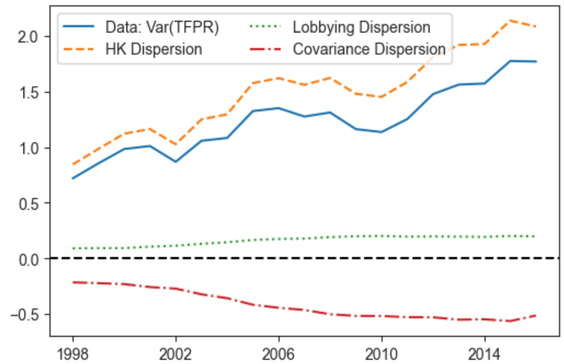


Figure 3.2: Decomposition of Dispersion of Measured TFPR

Notes. X-axis represents year and Y-axis represents each dispersion defined in Equation (3.15). The blue line is the dispersion of TFPR observed from the data. The orange, green, and red lines represent the HK, lobbying and covariance dispersion. The sum of HK, lobbying, and covariance dispersion is equal to the observed level of TFPR dispersion represented by the blue line.

Table 3.5: Relative TFP and Welfare of the Lobbying Economy to the Exogenous Wedge Economy

	Baseline	Free Entry	$\theta = 0.076$	$\theta = 0.045$	$\theta = 0.11$
	(1)	(2)	(3)	(4)	(5)
TFP (%)	7.10	3.98	7.90	7.25	3.98
Welfare (%)	7.14	3.38	7.94	7.28	4.00

Notes. This table presents relative TFP and welfare of the lobbying economy to the exogenous wedge economy. In column (1), the baseline calibrated parameters are used. In column (2), the free entry condition is imposed. In columns (3), (4), and (5), θ is set to be 0.075, 0.045, and 0.11.

The decomposition results are shown in Figure 3.2. The HK dispersion is larger than the overall TFPR dispersion observed in the data. This is because even though the lobbying dispersion is always positive, the covariance dispersion is sufficiently negative to decrease the pre-lobbying HK dispersion.[40] This implies that among publicly traded firms, the more productive firms tend to face higher exogenous distortions. Lobbying decreases the HK dispersion to the observed TFPR dispersion level, which is an average reduction of approximately 17%.

[40] Across the sample period, the mean observed variance of TFPR is 1.24. Note that this is larger than Hsieh and Klenow (2009) in which they use Census establishment data. The averages of the covariance, lobbying, and HK dispersion are -0.42, 0.16, and 1.5, respectively.

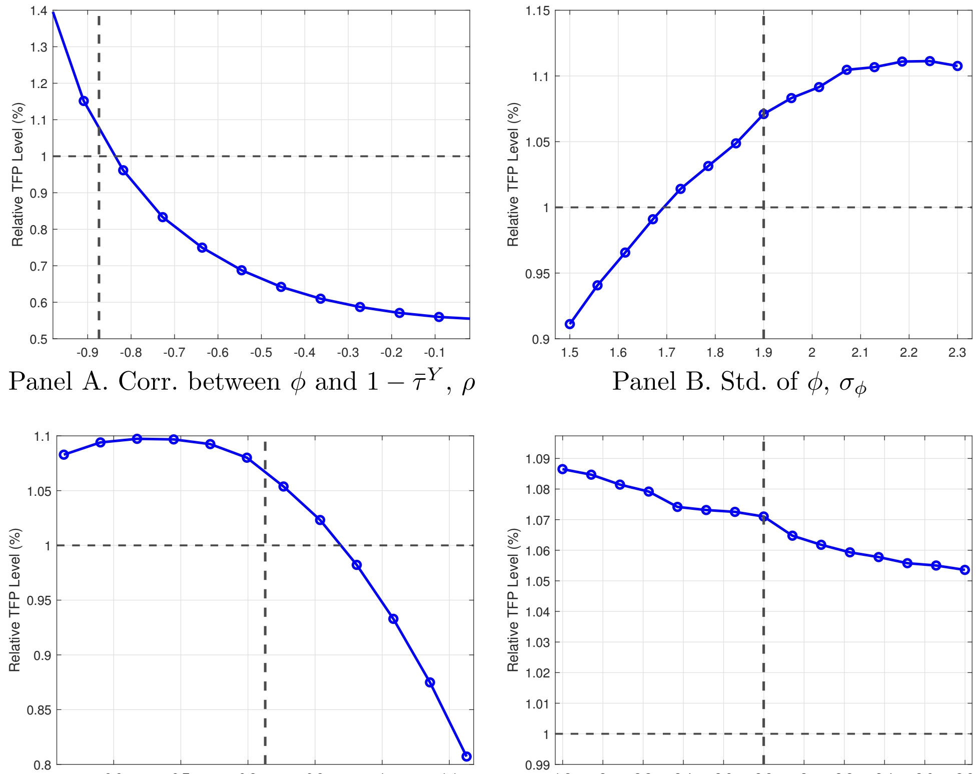
TFP and Welfare. I examine the effect of lobbying on TFP and welfare using the quantitative model. TFP is defined as real GDP per capita, which requires a producer price index (PPI). PPI is defined as $PPI = (\int_{\omega \in \Omega_{US}} p(\omega)^{1-\sigma} d\omega)^{(1/(1-\sigma))}$ where Ω_{US} is the set of domestic intermediate producers available in the US.[41] Column (1) of Table 3.5 reports relative TFP and welfare of the lobbying economy to the exogenous wedge economy. TFP and welfare of the lobbying economy are 7.10% and 7.14% higher than those of the exogenous wedge economy. In column (2), I conduct the same analysis under the free entry condition. The entry cost is normalized to 1 in Home and the entry cost of Foreign is set to 0.14 following Bollard et al. (2016), so that entry cost is proportional to GDP per capita.[42] Under the free entry condition, TFP and welfare gains from lobbying are 3.98% and 3.38%, lower than the baseline results in column (1).[43] Columns (3), (4), and (5) report the results with different values of θ. In column (3), I set $\theta = 0.76$ which is the estimate when using $\log(1 - ETR)$ in columns (3)-(4) of Table 3.2. In column (4), I set $\theta = 0.045$ and in column (5), I set $\theta = 0.11$. The results are robust for a wide range of θ.

Sensitivity Analysis. I examine the relative TFP of the lobbying economy to the exogenous wedge economy while varying one parameter and holding other parameters constant. The results for ρ, σ_ϕ, $\sigma_{\bar{\tau}^Y}$ and σ_η are reported in Panels A, B, C, and D of Figure 3.3. The vertical black line represents the calibrated parameter values. As the model predicts, Panel A shows that lobbying can mitigate misallocation from the exogenous wedges for a sufficiently low value of ρ near the calibrated value, but the concentration and amplification effects begin to dominate above -0.8. Panel B

[41] In a closed economy, this definition is equivalent to output per worker in Section 3.2.1. Burstein and Cravino (2015) discusses issues regarding the measurement of price index and real GDP in an open economy.

[42] Bollard et al. (2016) finds that entry cost increases with productivity. I set the entry cost of Foreign to be 0.14 (=1/7.2), where 1/7.2 is the US and top 15 trading countries' population ratio.

[43] Under the free entry condition, lobbying by a few big firms may block small firms' entry, which may lower the gains from lobbying.



Panel A. Corr. between ϕ and $1-\bar{\tau}^Y$, ρ

Panel B. Std. of ϕ, σ_ϕ

Panel C. Std. of $1-\bar{\tau}^Y$, $\sigma_{\bar{\tau}^Y}$

Panel D. Std. of η, σ_η

Figure 3.3: TFP. Exogenous Wedge Economy vs. Lobbying Economy

Notes. This figure displays relative TFP of the lobbying economy to the exogenous wedge economy. The vertical line represents the calibrated parameter. The results are based on the calibrated parameters reported in Table 3.3.

shows that the gains from lobbying become larger when σ_ϕ is above 1.7. Holding ρ fixed, higher σ_ϕ indicates that the more productive firms are more likely to face a higher exogenous distortion, which gives more room for lobbying to improve TFP. Panel C illustrates that as $\sigma_{\bar{\tau}^Y}$ increases, lobbying worsens the economy through the amplification effect. Lastly, in Panel D, as σ_η increases, lobbying decreases gains from lobbying because less productive firms can participate in lobbying if they draw low fixed lobbying costs.

3.4 Globalization

This section first provides empirical evidence that the China shock affected firm lobbying decisions and then quantitatively assesses the impact of globalization on aggregate TFP through lobbying channels.

3.4.1 Empirical Evidence regarding Globalization and Lobbying

I provide empirical evidence that a decrease in market size decreases the lobbying of small- and medium-sized firms. I use the rise in the Chinese import exposure as an exogenous shock to US firm market size (Autor et al., 2013; Acemoglu et al., 2016). China's productivity growth and a decrease in bilateral trade costs with the US have dramatically increased US imports from China after China joined the WTO in 2001.[44] Following Acemoglu et al. (2016), the China shock is defined as follows:

$$China^{oc,im}_{jt} = 100 \times \frac{IM^{oc,im}_{jt}}{Y^{US}_{jt_0} + IM^{US}_{jt_0} - EX^{US}_{jt_0}} \tag{3.16}$$

for industry j at time t. $IM^{oc,im}_{jt}$ is the sum of imports of other developed countries from China.[45] The denominator is the initial US domestic absorption at the start of the sample period, which is the sum of gross output $GO^{US}_{jt_0}$ and the total exports $EX^{US}_{jt_0}$ minus the total imports $IM^{US}_{jt_0}$. $China^{oc,im}_{jt}$ captures the exogenous market decrease of US firms driven by the China supply shock orthogonal to the US domestic demand shocks or firm-level conditions.

Figure 3.4 summarizes the main empirical findings. Based on the medians of the import exposure and the initial sales, firms are divided into four groups, as shown in Figure 3.4. The initial sales level is used as a proxy for firm size. Figure 3.4 shows that the gap in lobbying between large- and small-sized firms is rising only in indus-

[44] For more on the China shock, see Autor et al. (2013); Acemoglu et al. (2016); di Giovanni et al. (2014); Pierce and Schott (2016); Handley and Limão (2017).

[45] Following Autor et al. (2013), these high-income countries include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

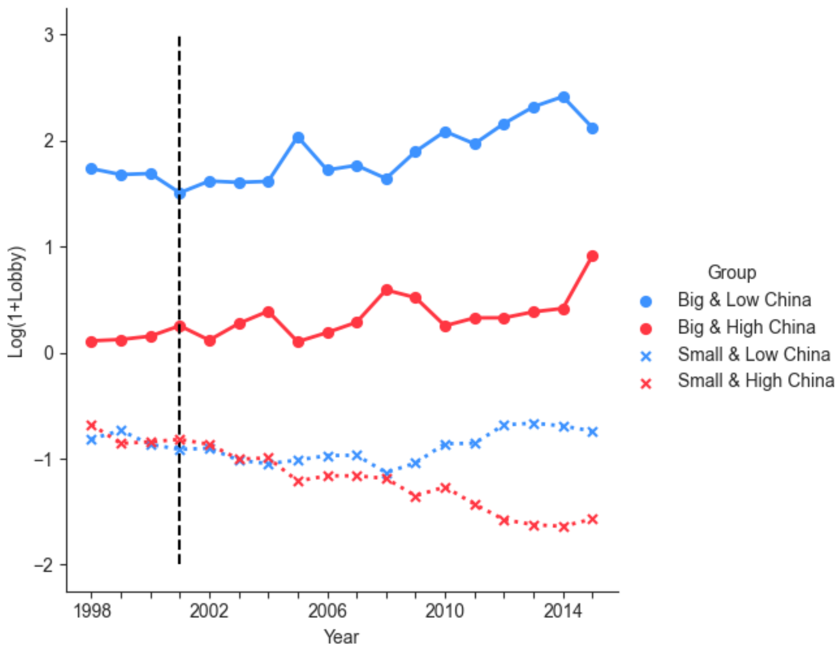


Figure 3.4: Trade-Induced Market Size Changes and Lobbying

Notes. The figure illustrates the average of log one plus lobbying of each group. Log one plus lobbying is residualized on firm and time fixed effects. Firms are grouped based on the medians of the distributions of the China shock defined in Equation (3.16) and the initial sales. If the import exposure of a firm's industry is above or below the median exposure across industries, it is categorized as "High China" or "Low China." If a firm's initial sales are above or below the median within 4-digit SIC code, it is labeled as "Big" or "Small." China's accession to the WTO in 2001 is denoted as the vertical black dashed line.

tries that are more exposed to import exposure after China joined the WTO. This indicates that the import shock has heterogeneous effects on lobbying, depending on firm size.

The graphical results are confirmed by the following long difference regression model.[46] For a firm i of industry j at year t,

$$\triangle y_{it} = \beta_1 \triangle China^{oc,im}_{jt} + \beta_2 \log(Sale_{it_0}) \times \triangle China^{oc,im}_{jt} + \delta_i + \delta_t + \triangle\epsilon_{it}, \tag{3.17}$$

where y_{it} is a dependent variable and $China^{oc,im}_{jt}$ is the import shock defined in Equation (3.16).[47] I use three main dependent variables log one plus lobbying, inverse

[46]In Appendix Section C.2.2, I provide the structural interpretation of the long difference regression model based on the model framework, which will be discussed in detail in the next section.

[47]Unlike Acemoglu et al. (2016) where $China^{oc,im}_{jt}$ is used as an instrumental variable, I estimate the model in a reduced-form, because the focus is to examine the reduced form relationship between market size and lobbying rather than giving a structural interpretation to the regression model.

hyperbolic sine transformation of lobbying $asinh(Lobby)$, and a dummy variable of positive lobbying multiplied 100.[48] The dummy dependent variable captures the extensive margin of lobbying. I control the interaction term between the log of the initial sales and the China shock to allow for heterogeneous effects of the China shock on firms of different sizes. I normalize the initial sales by the minimum value within 4-digit SIC industry so that β_1 can be interpreted as the effect of the import exposure on the firm with the minimum initial sales. I control for firm and time fixed effects to account for firm-specific trends and macroeconomic shocks. Given that lobbying is a long-term investment and may change alongside US political cycles, I average the samples over six years following the six-year terms of US senators.[49] All standard errors are clustered on 3-digit SIC industries. This allows an arbitrary correlation between the error terms of firms in the same 3-digit code.

Panel A of Table 3.6 reports these results. The dependent variable is log one plus lobbying in columns (1) and (2), $asinh(Lobby)$ in columns (3) and (4), and a dummy variable of positive lobbying in columns (5) and (6). In columns (2), (4), and (6), I control for state-specific time fixed effects to account for omitted confounding factors at the state level. Across specifications, I find sizable heterogeneous responses to the import exposure. In columns (1) and (3), for the firm at the 25th percentile of the initial sales distribution, a one standard deviation of the import exposure decreases 0.4 standard deviations of the log of one plus lobbying and a similar magnitude for $asinh(Lobby)$. However, lobbying of firms whose initial sales are above the 75th percentile is not affected by the import exposure.[50] Regarding the extensive margin

[48] Using a log of one plus lobbying can be misleading as it imposes strong functional form. The inverse hyperbolic sine function is defined as $\log(x + \sqrt{x^2+1})$. This is well-defined at zero and parallels the natural logarithm for positive values (Card and Dellavigna, 2020). I multiplied the dummy dependent variable by 100 so that the estimated coefficient can be interpreted as the percentage changes.

[49] For example, lobbying can decrease near the end of a senator's terms of office because of uncertainty regarding the results of the next election.

[50] This is calculated as $35 * (4.66 * 0.01 - 0.089)/3.74$ where 35 and 3.74 are the standard deviations of the import exposure and log of one plus lobbying. 4.66 is the initial sales level at the 25th percentile normalized by the minimum

in column (5), a one standard deviation of the import exposure decreases a firm's probability of lobbying by 37% but has negligible effects on firms whose initial sales exceed the 75th percentile. When controlling for state-specific time fixed effects in columns (2), (4), and (6), the coefficients retain the same signs and remain within the standard error of the baseline results in columns (1), (3), and (5).

The empirical finding is consistent with the complementarity between market size and lobbying, as stated in Proposition III.3. This proposition implies that firms in industries that are more exposed to the China shock decrease their lobbying amounts on average because of decreases in market size and the effects are heterogeneous depending on firm size.

Export Exposure. In addition to US imports from China, US exports to China increased after China became a member of the WTO.[51] If market size is an important determinant of lobbying, an increase in exports should increase firm lobbying expenditures in the direction opposite to the import exposure. To examine the effect of an increase in exports on a firm's lobbying, I additionally control for the US export exposure and its interaction with firm size, similar to the import exposure. Following Feenstra et al. (2019), I define the US export exposure as the relative export intensity:

$$China_{jt}^{oc,ex} = \frac{EX_{jt}^{oc,ex}}{GO_{jt_0}^{US}}, \tag{3.18}$$

where $EX_{jt}^{oc,ex}$ is defined as the sum of eight developed countries' exports to China relative to the US gross output of the industry at the start of the sample period, analogous to the import exposure measure.

sales within industry.

[51] Feenstra et al. (2019) finds that the expansion of the US exports to China increased the number of jobs of the US.

Panel B of Table 3.6 reports the results when controlling for the export exposure. The estimated coefficients of import exposure and its interaction have a larger magnitude and are estimated more precisely than the estimates without controlling for the export exposure. The heterogeneous effects of the export exposure are in the opposite direction to the import exposure, which is consistent with the market size effect. This effect predicts that marginal firms that were unable to export initially but could enter the Chinese market after a substantial reduction in bilateral trade costs may receive the largest benefit from market expansion due to extensive margin changes. The estimated coefficient of the interaction term in column (1) implies that a one standard deviation increase in the export exposure increases lobbying of a firm at the 25th and 75th percentile by 0.22 and 0.07 standard deviation of log one plus lobbying, decreasing their gap by 0.15 standard deviation. In column (3), I obtained a similar magnitude for $asinh(Lobby)$. For the extensive margin of lobbying in column (5), the export exposure has zero effect for the firm at the 75th percentile but increases the probability of lobbying for a firm at the 25th percentile by 6%. When controlling for state-specific time fixed effects in columns (2), (4), and (6), the estimated coefficients retain the same sign and all remain within the standard error of the baseline results.

Non-Trade-Related Lobbying. If firms systematically change their lobbying patterns against trade with China, the empirical results may be driven by trade-related lobbying activities rather than the market size effect. I provide evidence that the results in Panel A are not driven by trade-related lobbying.[52] I conduct the same analysis with non-trade-related lobbying expenditures. To identify whether a firm's lobbying

[52]Suppose special interests lobby to influence an incumbent government's trade policy against rising Chinese import competition. In such cases, the regression results may be driven by political factors rather than market size.

is related to trade, I use the general issue codes and summaries of lobbying activities, which are required to be reported by the Lobbying Disclosure Act. First, lobbying is classified as trade-related lobbying if its issue code is either TRD or TAR, where TRD covers general trade-related issues except for tariffs, and TAR covers issues related to tariffs.[53] Second, I also count any lobbying reports that mention "China" in their summary as trade-related lobbying because firms may lobby to increase trade barriers against Chinese imports using domestic policies that are seemingly non-trade-related. For example, firms may lobby for the strengthening of intellectual property rights or environmental regulations against Chinese firms, which may not be reported as trade-related issues in lobbying reports. Non-trade-related lobbying expenditures are obtained as the total lobbying expenditure minus the total trade-related lobbying expenditure. Panel C of Table 3.6 reports these results. The estimated coefficients are qualitatively and quantitatively similar to the results of Panel A up to two decimals, implying that the results are unlikely to be driven by trade-related lobbying activities.[54]

Non-Parametric Regressions. The interaction term implies that heterogeneous effects are linear in the log of initial sales. This imposed linearity can be misleading if the effects are highly nonlinear. To examine whether the results are driven by the functional form assumption, instead of using the linear interaction term, I use interaction terms between the Chinese import exposure and a dummy of a group of firms defined based on the tercile of the initial sales distribution within each industry,

[53] TAR was added in 2009. Before 2009, TAR covered both general trade-related issues and tariff-related issues. On many occasions, multiple issues are covered by one report, and only the total expenditures are reported per each report. In this case, lobbying expenditures per each issue are not separately identifiable from the total expenditures, so I obtain the lobbying expenditure per issue as the total expenditure divided by the number of issues. Online Appendix Figure C.1 and C.2 display how lobbying expenditures, general issue codes, and summaries are reported in the lobbying reports.

[54] In Online Appendix Table C.3, I run the same regression with trade-related lobbying as dependent variables. I find no significant effects of the import and export exposure on trade-related lobbying.

Table 3.6: Market Size and Lobbying

Dep.	$\log(1+Lobby)$		$asinh(Lobby)$		$100 \times 1[Lobby > 0]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline						
$China^{im}_{oc,jt}$	-0.079*	-0.089**	-0.084*	-0.094**	-0.674*	-0.749**
	(0.041)	(0.040)	(0.043)	(0.042)	(0.349)	(0.339)
$\triangle China^{oc,im}_{jt}$	0.010**	0.010**	0.010**	0.011**	0.079**	0.080**
$\times \log(Sale_{it_0})$	(0.004)	(0.004)	(0.005)	(0.005)	(0.037)	(0.037)
Panel B. Export Exposure						
$China^{im}_{oc,jt}$	-0.167***	-0.165***	-0.176***	-0.175***	-1.378***	-1.358***
	(0.026)	(0.031)	(0.028)	(0.033)	(0.240)	(0.278)
$\triangle China^{oc,im}_{jt}$	0.020***	0.019***	0.021***	0.020***	0.157***	0.147***
$\times \log(Sale_{it_0})$	(0.004)	(0.004)	(0.004)	(0.004)	(0.031)	(0.035)
$China^{ex}_{oc,jt}$	0.057***	0.057***	0.061***	0.060***	0.490***	0.477***
	(0.016)	(0.020)	(0.017)	(0.021)	(0.130)	(0.165)
$\triangle China^{oc,im}_{jt}$	-0.005**	-0.005**	-0.006***	-0.006**	-0.049***	-0.048**
$\times \log(Sale_{it_0})$	(0.002)	(0.002)	(0.002)	(0.002)	(0.016)	(0.019)
Panel C. Non-Trade-Related Lobbying						
$China^{oc,im}_{jt}$	-0.080**	-0.091**	-0.085**	-0.096**	-0.665**	-0.743**
	(0.039)	(0.038)	(0.041)	(0.040)	(0.333)	(0.327)
$\triangle China^{oc,im}_{jt}$	0.011**	0.011**	0.011**	0.011**	0.083**	0.083**
$\times \log(Sale_{it_0})$	(0.004)	(0.004)	(0.005)	(0.005)	(0.036)	(0.036)
Panel D. Non-Paramtetric Regressions						
$D^1 \times China^{oc,im}_{jt}$	-0.077*	-0.082**	-0.081*	-0.088**	-0.684**	-0.745**
	(0.040)	(0.039)	(0.042)	(0.042)	(0.334)	(0.329)
$D^2 \times China^{oc,im}_{jt}$	-0.004	-0.001	-0.004	-0.001	-0.022	0.001
	(0.027)	(0.032)	(0.028)	(0.034)	(0.239)	(0.289)
$D^3 \times China^{oc,im}_{jt}$	0.031	0.018	0.032	0.018	0.170	0.051
	(0.031)	(0.033)	(0.033)	(0.035)	(0.263)	(0.277)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	Y	N	Y	N
State × Time FE	N	Y	N	Y	N	Y
N	2770	2716	2770	2716	2770	2716

Notes. Panels A, B and C of the table reports results from estimating Equation (3.17) using OLS. Panel D reports results from estimating Equation (3.19) using OLS. The dependent variables are log one plus lobbying expenditures in columns (1) and (2), the inverse hyperbolic sine transformation of lobbying expenditures in columns (3) and (4) and a dummy variable of positive lobbying expenditures multiplied by 100 in columns (5) and (6). In Panel C, I use non trade-related lobbying expenditures as dependent variables. $China^{oc,im}_{jt}$ and $China^{oc,ex}_{jt}$ are defined in Equations (3.16) and (3.18). In all specifications, firm fixed effects are controlled. Samples are averaged over six years. Robust standard errors are reported in parentheses and clustered on 3-digit SIC industries. * p<0.1; ** p<0.05; *** p<0.01.

which may capture nonlinearity more flexibly than the linear interaction term. The specification is as follows.

$$\triangle y_{it} = \sum_{q=1}^{3} \beta^q D_i^q \times \triangle China_{jt}^{oc,im} + \delta_i + \delta_t + \triangle \epsilon_{it}, \tag{3.19}$$

where D_i^q is a dummy variable for each group $q = 1, 2, 3$ defined based on the tercile. β^q captures the average heterogeneous effects for each group.

The results are reported in Panel D of Table 3.6. Only the bottom group below the lowest tercile was negatively affected by the import exposure. The estimated coefficients in columns (1) and (3) imply that a one standard deviation increase in the import exposure decreases 0.75 standard deviations of the log of one plus lobbying and a similar magnitude for $asinh(Lobby)$. The coefficient in column (5) indicates that a one standard deviation increase in the import exposure decreased the probability of lobbying by 26% for the bottom group. When controlling state-specific fixed effects in columns (2), (4), and (6), the estimated coefficients all have the same sign and stay within the standard error of the results of columns (1), (3), and (5).

Additional Robustness Checks. I provide a battery of robustness checks. I run the analysis without averaging the sample and using initial employment or capital as alternative proxies for firm size. The results are reported in Panels A and B of Online Appendix Table C.2. The estimated coefficients are consistent with the baseline specification.

3.4.2 Quantitative Analysis

Gains from Trade. TFP gains from trade in the lobbying economy can be decomposed as follows:

$$
\begin{aligned}
(3.20)\quad & \underbrace{log(TFP^{T}_{lobby}) - log(TFP^{A}_{lobby})}_{\substack{\text{Gains from trade}\\ \text{in the lobbying economy}}} = \underbrace{\left\{log(TFP^{T}_{exo}) - log(TFP^{A}_{exo})\right\}}_{\substack{\text{Gains from trade}\\ \text{in the exogenous wedge economy}}} \\
& + \underbrace{\underbrace{\left\{log(TFP^{T}_{lobby}) - log(TFP^{T}_{exo})\right\}}_{\substack{\text{Gains or losses from lobbying}\\ \text{when opening to trade}}} - \underbrace{\left\{log(TFP^{A}_{lobby}) - log(TFP^{A}_{exo})\right\}}_{\substack{\text{Gains or losses from lobbying}\\ \text{in autarky}}}}_{\substack{\text{Changes of TFP influences:}\\ \text{Trade opening vs. Autarky}}},
\end{aligned}
$$

where the superscripts T and A denote trade opening and autarky, respectively. TFP gains from trade in the lobbying economy are the sum of the following three terms: (1) gains from trade in the exogenous wedge economy, (2) gains or losses from lobbying in ane open economy, and (3) gains or losses from lobbying in autarky. The simple algebra shows that the difference between gains from trade in the lobbying and exogenous wedge economy is the difference between gains from lobbying of the lobbying economy in an open economy and autarky. The difference between gains from lobbying in an open economy and autarky measures the extent to which opening to trade affects the TFP influences of lobbying. If opening to trade increases the TFP influences of lobbying, gains from trade in the lobbying economy would be larger than those in the exogenous wedge economy, and vice versa.

Table 3.7 reports on TFP and welfare gains from trade in the different economies, comparing autarky to an open economy with calibrated parameters. Compared to autarky, when opening of trade to the observed import level in the data, TFP increases by 4.13%, 4.23%, and 2.68% in the lobbying, exogenous wedge, and efficient economies. In both distorted economies, gains from trade are larger than gains from

Table 3.7: International Trade and Lobbying. Opening to Trade

	Lobbying Economy (A)	Exogenous Wedge Economy (B)	Efficient Economy	Changes of TFP influences (A) - (B)
	(1)	(2)	(3)	(4)
Panel A. Opening to Trade, $\tau_x = \infty \Rightarrow \tau_x = 1.7$				
TFP (%)	4.13	4.23	2.68	-0.10
Welfare (%)	3.07	3.13	1.96	-0.07
Panel B. Before and After the China shock				
TFP (%)	2.26	2.34	1.58	-0.08
Welfare (%)	2.76	2.84	2.01	-0.08

Notes. This table presents gains from trade in different economies. Panel A reports changes of welfare and TFP when opening to trade. Panel B reports changes of welfare and TFP before and after the China shock. Column (4) reports the difference of TFP and welfare gains between the lobbying and exogenous wedge economies. All the results are based on the calibrated parameters reported in Table 3.3

trade in the efficient economy.[55] Column (4) presents the changes of the TFP influences, which is equivalent to the difference between gains from lobbying in autarky and an open economy. Compared to autarky, the gains from lobbying decrease by 0.1% because the concentration and amplification effects are exacerbated in the open economy. As lobbying expenditures become more unequally distributed in the open economy than autarky, this leads to too much input concentrated toward big-sized lobbying exporters, exacerbating the concentration and amplification effects.[56] Welfare can be decomposed in the same way, and there is a -0.07% reduction in welfare gains from lobbying in the open economy relative to autarky.

The China Shock. I evaluate the impact of the China shock on the aggregate TFP and welfare. The China shock is modeled as an increase in the mean level of Foreign productivity μ_ϕ^F. I fit μ_ϕ^F to the changes in the US import share with the 15 main trading countries. The manufacturing import share rose from 0.12 to 0.20 during the sample period, more than 55% from increases in imports from China. In the China

[55] Bai et al. (2019) and Berthou et al. (2018) also show that idiosyncratic distortions can affect the gains from trade.

[56] In the simulated data based on the model with the baseline parameters, the variance of $\log(1 + b_{it}^*)$ is 2.22 and 2.26 in autarky and the open economy. The variance of the open economy is 1.5% higher, implying that lobbying expenditures across firms become more unequal when opening to trade.

shock counterfactual, I set μ_{ϕ}^{F} 53% higher so that the model fits the 67% increase in import share (0.20/0.12). Panel B in Table 3.7 presents these results. Welfare and TFP gains of the lobbying economy are larger than those of the efficient economy. After the China shock, TFP and welfare increased by 2.26% and 2.76%, and 1.58% and 2.01% in the efficient economy. After the China shock, both the TFP and welfare gains from lobbying decreased by -0.08%.

3.5 Conclusion

This paper evaluates the effects of lobbying on resource misallocation and aggregate TFP. I theoretically characterize the conditions under which lobbying increases or decreases TFP and provide a quantitative framework to evaluate the impact of lobbying under pre-lobbying exogenous distortions. The model developed here allows for the separate identification of the pre-lobbying exogenous wedge and the endogenous wedge and for the quantification of the effect of lobbying on aggregate TFP and welfare. Lobbying can improve TFP when the more productive firms face a higher pre-lobbying exogenous distortion because, in such cases, they can lobby to overcome that initial distortion. Although lobbying is seemingly distortionary at the micro-level, the aggregate implication of this activity can differ from the conventional wisdom, which implies the importance of considering the general equilibrium effects of lobbying.

From the firm-level data, I quantitatively find that lobbying can increase the aggregate TFP of the US economy by 4-7%. In addition, I find that international trade may affect firm lobbying decisions through the market size effect and, in turn, have an impact on aggregate TFP. The effect of trade on firm lobbying is supported by the reduced-form empirical evidence. I find that the China shock decreased small-sized firms' lobbying. Also, I quantitatively find that opening to trade can decrease the positive TFP influence of lobbying by 0.1%.

A caveat of this quantification exercise is that Compustat covers only publicly traded firms, which means that the data might not be representative of the entire US economy. Also, the model does not incorporate other important features of lobbying, such as strategic behaviors between firms and increasing barriers to entry by incumbents. Enriching both the data and the theory components to study the impact of lobbying on misallocation remains a fruitful avenue for future research.

APPENDICES

APPENDIX A

Appendices to Chapter 1

A.1 Appendix: Data

A.1.1 Data on Technology Adoption

ARTICLE III. SUPPLY OF TECHNICAL ASSISTANCE

1. MITSUI TOATSU shall transmit in documentary form to KOLON, TECHNICAL INFORMATION.

2. MITSUI TOATSU shall provide, upon the request of KOLON, the services of its technical personnel to assist KOLON in the engineering, construction and operation of the PLANT and in the quality and production control of LICENSED PRODUCT.

KOLON shall, for such services of technical personnel, pay the reasonable salaries, travelling and living expenses of such technical personnel while away from their own factories and offices.

The number of such technical personnel, the period of the services and the payment shall be discussed and decided separately between the parties.

3. MITSUI TOATSU shall receive KOLON's technical trainees at a plant designated by MITSUI TOATSU in order to train them

Figure A.1: Example. A Contract between Kolon and Mitsui Toatsu

Institutional Background of Technology Adoption Contract Documents. After Chung-Hee Park came to power through a military coup, he created the Economic Planning Board (EPB) in 1961 to promote economic development and design better economic policies. President Park was in power for 19 years. He was the chairman of the military junta for 1961 and 1962. In 1963 and 1967, he was elected a president of the civilian government. In 1971, he was re-elected for what was supposed to be his last presidency. In 1972, President Park declared martial law and amended the country's constitution into an authoritarian document, called the Yushin constitution, which extended his term of office as president indefinitely. After 1961 and until President Park was assassinated in 1979, the EPB was at the center of South Korea's economic policy making process.

During his presidency, the Foreign Capital Act strictly regulated domestic firms' transactions with foreign firms, including technology adoption contracts. The law required South Korean firms to obtain approval from the EPB before they made contracts to adopt new technology from foreign firms. They also had to submit documentation of their plans for using the technologies they adopted and copies of the contracts. Beginning in 1961 and continuing until the mid-1980s, the EPB met every month. In each meeting, they examined new contracts between domestic and foreign firms. The National Archives of Korea collected and preserved the documents the EPB examined in its monthly meetings. Most of our technology adoption data mainly comes from historical contract documents from the National Archives of Korea.

Figure A.1 is one page from a contract document between Kolon (South Korean) and Mitsui Toatsu (Mitsui) (Japanese). Most of the adopted technologies involved the transfer of knowledge about how to build and operate plants and capital equipment related to mass production. For example, Figure A.1 specifies that Mitsui had to provide blueprints, send skilled engineers to train South Korean workers, and provide training service by inviting South Korean engineers to its plants in Japan.

One may wonder why foreign firms were selling technology to Korean firms in the 1970s although South Korean firms that adopted technologies from these foreign firms could have been a future competitor in international markets. An example of technology contracts between Pohang Iron and Steel Company (POSCO), a South Korean company, and Nippon Steel Company (NSC), a Japanese company, might explain this. POSCO made a technology contract about construction and operation of integrated steel mills. NSC sent its skilled engineers to teach Korean engineers of POSCO how to run integrated steel mills.

First, NSC could earn a lot of profits from this contract. The fixed fee that POSCO had to pay for the contract accounted for 20% of the total annual export of plant engineering of NSC. Second, NSC did not transfer state of the art technology but more standardized technology that were widely used in developed countries. For example, NSC refused to transfer technology related to the computerization of production system, which was considered to be state of the art at that time. In the early 1980s when POSCO grew fast and became a big competitor in international steel markets, NSC refused to make further official technology contracts with POSCO. Third, foreign firms did not expect that South Korean firms would absorb technology within such a short period of time. The CEO of NSC, Eishiro Saito, said that he did not expect remarkably high rates of POSCO's technology absorption and said in his interview that technology adoption contracts between the two firms hit NSC like a boomerang (Chosun-ilbo, 1976. 11. 23).

Available Information. From these contracts, we obtained three main pieces of information: names of domestic firms, names of foreign firms, and contract years. We use the information on names of domestic firms and contract years to construct a dummy variable of firms' adoption status. We use information on the names of foreign firms to match them to the USPTO.

A.1.2 Firm Balance Sheet Data.

We match firm balance sheet data obtained from the Annual Reports of Korean Companies between 1970 and 1982. These reports are published by the Korea Productivity Center. We obtain firms' balance sheet variables and locations of production from these reports.

Balance Sheet Variables. The information from balance sheet includes sales, assets, fixed assets, and employment. Employment data does not begin until 1972. We convert all monetary values into 2015 US dollars. The dataset covers firms with more than 50 employees. The dataset also includes information on firms' start years. We use this start year information to trace changes in firm names.

Location of Production. The dataset includes detailed information on the address of the location of production. We convert addresses to the 2010 administrative divisions of South Korea up to the town level. (We classify firms' location of production into villages (li) and neighborhood (dong) levels. Then, using distance between towns, we calculate distance between firms within the same district.

Sector Groupings. We classify firms into 10 manufacturing sectors. We classify four as heavy manufacturing sectors, largely following the sector classification in Lane (2019). Table A.1 reports the classification. It is similar to the classification in Choi and Levchenko (2021), who used the same firm balance sheet data. The numbers inside the parenthesis are ISIC Rev. 3.1 (ISIC) codes. We use these ISIC codes to map our firm data to other trade or tariff data.

A.1.3 Other datasets

United States Patent and Trademark Office (USPTO). We use the USPTO data to measure foreign firms' patenting activities.[1] We match the USPTO with foreign contractors in our dataset using their names. Our matching procedure proceeds as follows.

- Step 1: Clean firms' names.
  - For example, we erase words like "Inc" or "Comp."
- Step 2: Fuzzy match firms' names from our dataset and the USPTO. We use the fuzzmatcher package in Python.
- Step 3: Hand-match firms that are not matched in the first step based on names.
- Step 4: For foreign firms that have different assignee IDs in the UPSTO but with the same ID (gvkey) in the Global Compustat, we give them a unique assignee ID and sum the numbers of patents and citations up to the Compustat ID level.
  - When we merge assignee IDs and gvkey, we use the matching constructed by Bena et al. (2017).

Input-Output Tables. We obtain input-output tables from the Bank of Korea. [2] Input-output tables are available for 1970, 1973, 1975, 1978, 1980, 1983, and 1985 during the sample period. We convert codes of the input-output tables into ISIC Rev. 3.1 (ISIC) codes.

[1] We download the dataset from `https://patentsview.org`.

[2] We download the data from Economic Statistics of the Bank of Korea, `https://ecos.bok.or.kr/EIndex_en.jsp`.

Table A.1: Classification of Sectors

	Aggregated Industry	Industry
Heavy Mfg.	(i) Chemicals, Petrochemicals, Rubber, & Plastic Products	Coke oven products (231) Refined petroleum products (232) Basic chemicals (241) Other chemical products (242) Man-made fibres (243) except for pharmaceuticals and medicine chemicals (2423) Rubber products (251) Plastic products (252)
	(ii) Electrical Equipment	Office, accounting, & computing machinery (30) Electrical machinery and apparatus n.e.c. (31) Ratio, television and communication equipment and apparatus (32) Medical, precision, and optical instruments, watches and clocks (33)
	(iii) Basic & Fabricated Metals	Basic metals (27) Fabricated metals (28)
	(iv) Machinery & Transport Equipment	Machinery and equipment n.e.c. (29) Motor vehicles, trailers and semi trailers (34) Building and repairing of ships and boats (351) Railway and tramway locomotives and rolling stock (352) Aircraft and spacecraft (353) Transport equipment n.e.c. (359)
Light Mfg.	(v) Food, Beverages, & Tobacco	Food products and beverages (15) Tobacco products (16)
	(vi) Textiles, Apparel, & Leather	Textiles (17) Apparel (18) Leather, luggage, handbags, saddlery, harness, and footwear (19)
	(vii) Manufacturing n.e.c.	Manufacturing n.e.c. (369)
	(viii) Wood, Paper, Printing, & Furniture	Wood and of products, cork (20) Paper and paper products (21) Publishing and printing (22) Furniture (361)
	(ix) Pharmaceuticals & Medicine Chemicals	pharmaceuticals and medicine chemicals (2423)
	(x) Other Nonmetallic Mineral Products	Glass and glass products (261) on-metallic mineral products n.e.c. (269)

OECD Stan Database. We obtain the cross-country data on heavy manufacturing's contributions to GDP in Figure 1.1 from OECD Stan database, which has sectoral GDP information at the two-digit ISIC3 level.[3]

For Mexico, the total GDP was not available for the early 1970s, but the total value of light and heavy manufacturing shares was available. Therefore, from the OECD Stan database, we can calculate heavy manufacturing sector's contribution to the manufacturing sector's GDP, but we could not calculate the sector's contribution to the national GDP. Thus, we supplement the Mexico sample with data on manufacturing's contribution to total GDP obtained from the World Bank Indicators.[4] We then obtained heavy manufacturing's share of GDP as that sector's share of the total value manufacturing added to the Mexican economy multiplied by the manufacturing sector's contribution to total GDP; that is,

$$\text{Heavy mfg.'s share of GDP} = \underbrace{\frac{\text{Heavy mfg. GDP}}{\text{Total mfg. GDP}}}_{\text{OECD STAN}} \times \underbrace{\frac{\text{Total mfg. GDP}}{\text{National GDP}}}_{\text{World Bank}}.$$

A.1.4 Criteria for Matching Two Main datasets

We match technology adoption and firm balance sheet datasets using firms' names and information about start year and sector. We match the two datasets based on the following criteria:

1. Firms should have the same name in a given year.
2. Firms should have begun operation before the years they adopted new technology.
    - Even if we observe the same names in both datasets, if adoption activities happened before start year information in the balance sheet data, we do

[3] We download the data from OECD, "STAN Database for Structural Analysis," `https://stats.oecd.org/Index.aspx?DataSetCode=STAN`.

[4] We download the data from World Bank, "Manufacturing, Value Added (%)," `https://data.worldbank.org/indicator/NV.IND.MANF.ZS`.

not match those firms.

3. Firms should be in the same sector.
    - Each contract document has a brief description about the technology firms adopted
    - Even if we observe the same names in both datasets, if these descriptions do not align with the recorded sector in the balance sheet data, we do not match those firms.

A.1.5 Tracking Changes of Firms' Names

One of the key challenges when merging two datasets based on firms' names is that many firms changed their names during the sample period. We tracked each firm's name in the Annual Reports of Korean Companies and in the history sections of the firms' websites. We also searched for firm names at `https://www.jobkorea.co.kr` and `https://www.saramin.co.kr`, which are the two largest job posting sites. We identified firm names as the same firm only if the information in the Annual Reports of Korean Companies matched information obtained on the Internet. We also searched in newspapers from the 1970s, which sometimes had articles that announced a firm's change of name. When a firm merged with another firm, we counted that as an exit.

A.1.6 Coverage.

Figure A.2 reports the average coverage of the firm-level data across different sectors. We report the ratio between the sum of all firms in each year divided by gross output from the input-output table for corresponding years. When we compute this coverage, we impute using the information on assets for some observations that lack

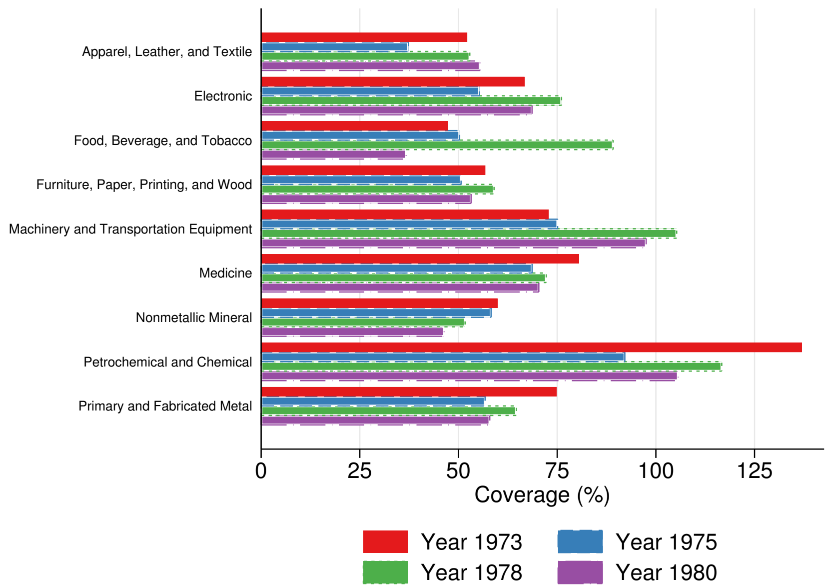


Figure A.2: Coverage of Manufacturing Sectors in Our Dataset
Notes. This figure plots the ratio of sectoral gross output from the input-output tables to the sum of firms' sales in corresponding sectors.

information about sales. For each sector j, we run the following regression model:

$$\ln(\text{Sales}_{it}) = \beta_j \ln(\text{Assets}_{it}) + \delta_t + \epsilon_{it}.$$

Using the estimated coefficient of β_j, we impute missing sales using $\hat{\beta}_j \ln(\text{Assets}_{it})$.

Across sectors, our dataset covers about 70% of gross output from the input-output table. However, there is some heterogeneity across sectors. Machinery and Transportation Equipment and Petrochemical and Chemical have higher coverage rates, whereas Food, Beverage, and Tobacco and Apparel, Leather, and Textile have relatively less coverage than other sectors.

A.1.7 An Example of a Loser

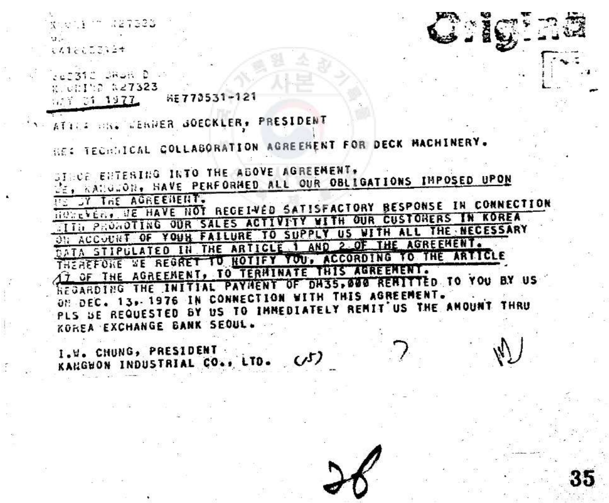
We identify losers from contract documents. The Foreign Capital Act required firms to submit related documents when their contracts failed if the EPB had approved the contract. They had to submit official cancellation contract documents and documents that described why the contract had failed.

Figure A.3 reports an example of a loser. Kangwon Industrial Co. (Kangwon) and the German firm Broehl Maschinen Fabric GmbH (Broehl) made a contract regarding deck machinery. Although Kangwon paid a fixed fee in advance, Broehl did not send a blueprint. Panel A is the English document related to the termination of the contract between two firms. Panel B is the Korean document in which Kangwon reported why the contract had failed. The document says that the contract failed because although Kangwon asked Broehl several times to fulfill the contract after Kangwan paid the fee, Broehl did not respond.

A.1.8 Descriptive Statistics.

Table A.2 reports the descriptive statistics of the constructed dataset. The table reports firm balance sheet variables, including log sales, assets, fixed assets, and employment, and variables related to firms' adoption activities. In columns (1), (2), and (3), we include samples of all manufacturing, heavy manufacturing, and light manufacturing firms. $\mathbb{1}$[Adopt] is a dummy variable that equals 1 if a firm is in a contractual relationship with any foreign firms. From the contract data, we observe when firms made adoption contracts and what years the contracts were made. The dummy variable equals 1 if a firm was under contract with a foreign firm. $\mathbb{1}$[Adopt] is a dummy variable that equals 1 if a firm ever adopted foreign technology during the sample period. Consistent with the historical narrative, adoption activities were concentrated among heavy manufacturing firms. In the period 1970 to 1982, an average of 13% of heavy manufacturing firms adopted technology at least once. Only 4.2% of light manufacturing firms adopted technology during that period.

In Panel A of Figure A.4, we have plotted the evolution of the size of the heavy



Original

RE770531-121

MAY 31 1977

ATTN: MR. WERNER JOECKLER, PRESIDENT

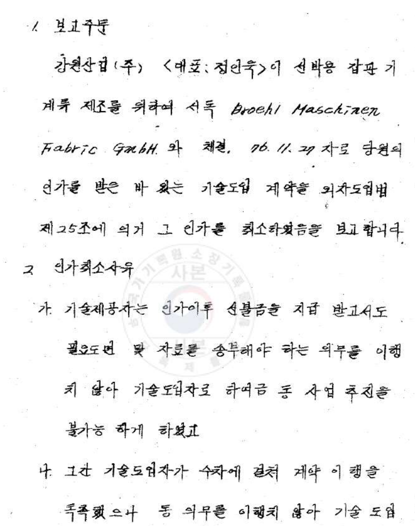
RE: TECHNICAL COLLABORATION AGREEMENT FOR DECK MACHINERY.

SINCE ENTERING INTO THE ABOVE AGREEMENT,
WE, KANGWON, HAVE PERFORMED ALL OUR OBLIGATIONS IMPOSED UPON
US BY THE AGREEMENT.
HOWEVER, WE HAVE NOT RECEIVED SATISFACTORY RESPONSE IN CONNECTION
WITH PROMOTING OUR SALES ACTIVITY WITH OUR CUSTOMERS IN KOREA
ON ACCOUNT OF YOUR FAILURE TO SUPPLY US WITH ALL THE NECESSARY
DATA STIPULATED IN THE ARTICLE 1 AND 2 OF THE AGREEMENT.
THEREFORE WE REGRET TO NOTIFY YOU, ACCORDING TO THE ARTICLE
17 OF THE AGREEMENT, TO TERMINATE THIS AGREEMENT.
REGARDING THE INITIAL PAYMENT OF DM35,000 REMITTED TO YOU BY US
ON DEC. 13, 1976 IN CONNECTION WITH THIS AGREEMENT.
PLS BE REQUESTED BY US TO IMMEDIATELY REMIT US THE AMOUNT THRU
KOREA EXCHANGE BANK SEOUL.

I.W. CHUNG, PRESIDENT
KANGWON INDUSTRIAL CO., LTD.

35

A. Documentation of the termination of the contract between Kangwan and Broehl



1. 보고주문

강원산업(주) <대표: 정인욱>이 선박용 갑판 기계류 제조를 위하여 서독 Broehl Maschinen Fabric GmbH.와 체결, 76. 11. 27자로 당원의 인가를 받은 바 있는 기술도입 계약을 외자도입법 제25조에 의거 그 인가를 취소하였음을 보고합니다.

2. 인가취소사유

가. 기술제공자는 인가이후 선불금을 지급 받고서도 필요도면 및 자료를 송부해야 하는 의무를 이행치 않아 기술도입자로 하여금 동 사업 추진을 불가능 하게 하였고

나. 그간 기술도입자가 수차에 걸쳐 계약 이행을 독촉했으나 동 의무를 이행치 않아 기술 도입

B. Document that explains the reason for the termination

Figure A.3: Example of a Loser Firm

Table A.2: Descriptive Statistics.

	All mfg. (1)	Heavy mfg. (2)	Light mfg. (3)
	Firm Balance Sheet		
ln(Sales)	15.65	15.54	15.75
	(1.925)	(1.938)	(1.910)
ln(Assets)	15.14	15.10	15.18
	(1.766)	(1.764)	(1.767)
ln(Fixed Assets)	13.96	13.94	13.98
	(1.966)	(1.933)	(1.992)
ln(Emp)	5.166	5.028	5.285
	(1.321)	(1.319)	(1.311)
	Technology Adoption		
$\mathbb{1}$[Adopt]	0.0587	0.0951	0.0267
	(0.235)	(0.293)	(0.161)
$\mathbb{1}$[Ever Adopt]	0.0841	0.132	0.0418
	(0.278)	(0.339)	(0.200)
N	43720	20497	23223

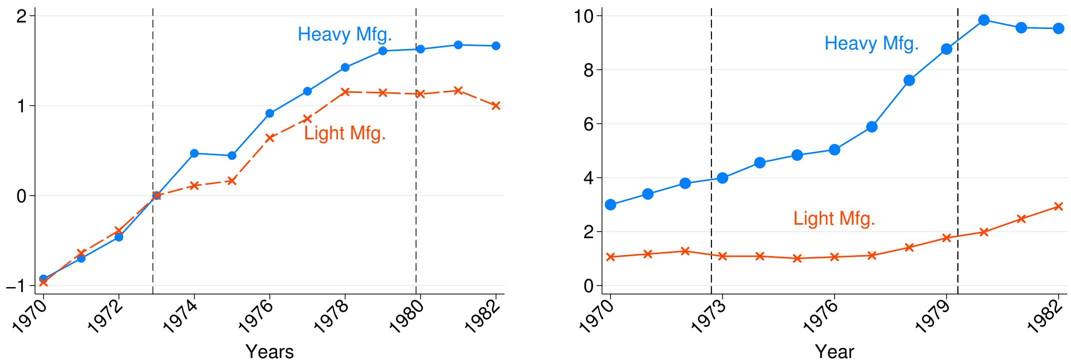
Notes. This table reports the descriptive statistics. All monetary values are in 2015 US dollars. $\mathbb{1}$[Adopt] is a dummy variable which equals one if a firm was in a technology adoption contract relationship with foreign firms in a given year. $\mathbb{1}$[Ever Adopt] is a dummy variable which equals one if a firm ever had technology adoption contracts with foreign firms.

and light manufacturing sectors. We measure the size of sector j as follows:

$$\ln Size_{jt} = \ln\left(\sum_{i \in j} Sale_{it}\right), \quad j \in \{\text{Light}, \text{Heavy}\}.$$

We normalize the size of each sector by their 1973 level so we can track how the heavy and light manufacturing sectors evolved differently after the adoption subsidy policy was implemented in 1973. In Panel B of Figure A.4, we have plotted shares of adopters in heavy and light manufacturing sectors. The shares are defined as firms that were in contractual relationships with foreign firms as a percentage of the total number of firms in a given year.

The patterns from the firm-level data reveal a similar pattern in Figure 1.1. The total size of heavy manufacturing sectors began increasing faster than that of the light manufacturing sectors after 1973, and this rapid increase coincided with increases in



A. log sum of sales

B. shares of adopters

Figure A.4: Evolution of Size of Manufacturing Sectors and Shares of Adopters from the Firm-Level Data

Notes. Panels A and B of this figure plot evolution of the size of manufacturing sectors and shares of adopters, respectively. The size of each sector is measured as a log of the total sum of firms' sales in each sector. We normalize the size of each sector by their levels in 1973. Shares of adopters are computed as shares of firms that were in a technology adoption contract with foreign firms in a given year. The two dotted vertical lines represent the start and the end of the South Korean government policy that subsidized technology adoption between 1973 and 1979.

the amount of new technology that heavy manufacturing firms adopted.

A.2 Appendix: Historical Background

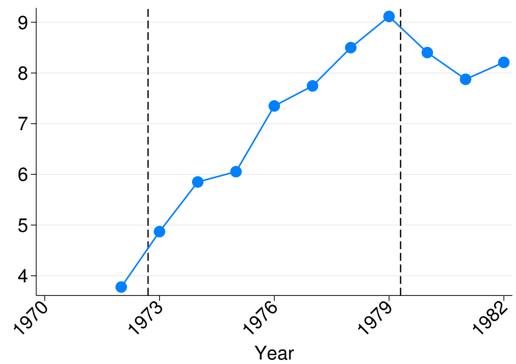
A.2.1 Additional Aggregate Statistics on Late Industrialization in South Korea

In this section, we provide additional aggregate patterns on late industrialization in South Korea in the 1970s. In Panels A, B, and C of Figure A.5, we report the heavy manufacturing employment share, the heavy manufacturing export share, and Balassa's revealed comparative advantage index, which is defined as:

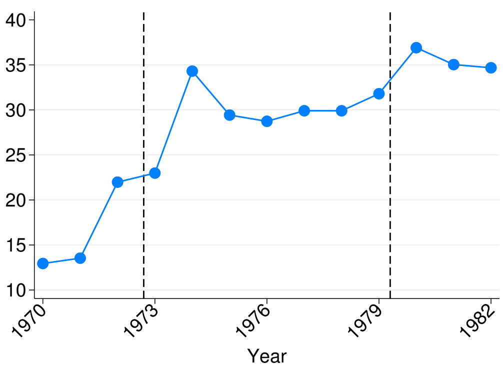
$$RCA_{heavy,t} = \frac{EX_{heavy,t}^{KOR} / \sum\limits_{j \in \mathcal{J}} EX_{jt}^{KOR}}{EX_{heavy,t}^{RoW} / \sum\limits_{j \in \mathcal{J}} EX_{jt}^{RoW}},$$

where EX_{jt}^{c} is the sector j exports of country c. $RCA_{heavy,t}$ compares specialization patterns in the heavy manufacturing sectors of South Korea to those of the rest of the world. We construct employment shares based on the OECD STAN Database. We use trade data from Feenstra et al. (2005) to compute export shares and the revealed comparative advantage index.[5] Consistent with the heavy manufacturing GDP shares in Figure 1.1, the employment shares increased from 4% in 1972 to 8% in 1982. Sectoral employment data for South Korea does not begin until 1972 in the OECD's STAN Database, so we could not compute the shares for 1970 and 1971. The export shares increased from 13.7% in 1972 to 35% in 1982.

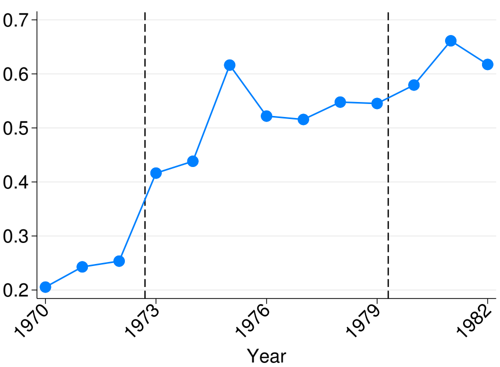
[5] We download the trade data from `https://cid.econ.ucdavis.edu/nberus.html`.



A. Heavy mfg. employment share (%)



B. Heavy mfg. export share (%)



C. Heavy mfg. Balassa index, RCA

Figure A.5: Aggregate Patterns of Late Industrialization in South Korea in the 1970s

Notes. The figure illustrates aggregate changes of the South Korean economy during the 1970s. Panels A, B, and C reports heavy manufacturing sector's employment shares, export shares, and the Balassa revealed comparative advantage index. The two dotted vertical lines represent the start and the end of the South Korean government policy that subsidized technology adoption between 1973 and 1979.

A.2.2 Evidence of the Effects of the South Korean Government Policy on Firms' Technology Adoption Decisions

In this section, we provide empirical evidence on the impact of the South Korean government policy on firms' technology adoption decisions. We run the following event study specification for the sample of heavy manufacturing firms:

$$100 \times \mathbb{1}[Adopt_{it}] = \sum_{\tau=-3}^{9} \beta^{\tau} D_t^{\tau} + \delta_i + \epsilon_{it},$$

where i denotes firm and t time. $\mathbb{1}[Adopt_{it}]$ is a dummy variable of firms' adoption status. We multiply the dummy variable by 100 for ease of interpretation. D_t^{τ} are the event study variables defined as $D_t^{\tau} := \mathbb{1}[t - \tau = 1973]$. δ_i are time-invariant firm fixed effects. ϵ_{it} are the error terms. Standard errors are clustered at regional level.

The key variables of interest are $\{\beta^{\tau}\}_{\tau=-3}^{9}$. We normalize β^0 to zero. Thus, β^{τ} captures how firms' adoption decisions differ relative to the 1973 level. If the policy affected firms' adoption decisions after the policy started to be implemented in 1973, we expect $\{\beta^{\tau}\}_{\tau=1}^{9}$ to be statistically significantly larger than zero. $\{\beta^{\tau}\}_{\tau=-3}^{-1}$ are pre-trends. If confounding factors drove the implementation of the policy, that may show up in the pre-trends. If there were no confounding factors, we expect these pre-trends to be statistically indistinguishable from zero. Because we are restricting our samples to be heavy manufacturing firms, time fixed effects are not separately identifiable from these event dummies.

Figure A.6 illustrates the estimated coefficients with 95 percent confidence intervals. There were no pre-trends. Firms' overall adoption decisions before 1973 were not statistically distinguishable from those in 1973. However, after 1973, more firms started adopting foreign technologies. The sudden rapid increase after 1973 supports the historical narrative of the sudden launch of the Heavy Chemical Industry Drive in response to a political shock. The estimated coefficients imply that the probability of adopting foreign technology in 1980 increased by 20 percentage points relative to 1973.

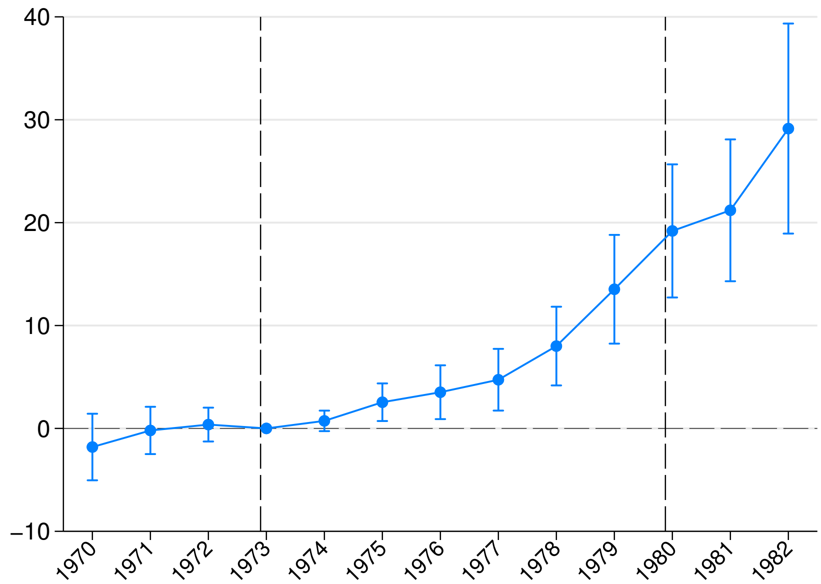


Figure A.6: The Impact of the Temporary Government Subsidies on Firms' Technology Adoption Decisions

Notes. This figure illustrates the estimated β^{τ}. β^{0} is normalized to zero. All specifications control for firm and calendar year fixed effects. The two dotted vertical lines represent the start and the end of the government policy that subsidized technology adoption from 1973 to 1979. Error bars represent 95 percent confidence intervals based on standard errors clustered at regional level.

A.3 Appendix: Model

A.3.1 Closed-Form Expressions for Regional Variables

In this section, we derive closed-form expressions for price index, regional gross output for domestic expenditures, and regional exports. Given optimal adoption and export decisions and the bounded Pareto distributional assumption, regional-level variables summed across firms within regions and sectors can be expressed as a function of shares of adopters, shares of exporters, subsidies, and natural advantage.

Price Index. A price index of sector j in region n is

$$P_{njt}^{1-\sigma} = \sum_{m \in \mathcal{N}} M_{mj} \times \Bigg\{ \underbrace{\int_{\phi_{mjt}^{min}}^{\bar{\phi}_{mjt}^{T}} \left(\frac{\sigma}{\sigma - 1} \frac{\tau_{mnj} c_{mjt}}{f(\lambda_{mjt-1}^{T}) \phi_{it}} \right)^{1-\sigma} dG_{mjt}(\phi_{it})}_{\text{Non-adopters' varieties}}$$

$$+ \underbrace{\int_{\bar{\phi}_{mjt}^{T}}^{\phi_{mjt}^{max}} \left(\frac{\sigma}{\sigma - 1} \frac{\tau_{mnj}(1 - s_{mjt}) c_{mjt}}{f(\lambda_{mjt-1}^{T}) \phi_{it}} \right)^{1-\sigma} dG_{mjt}(\phi_{it})}_{\text{Adopters' varieties}} \Bigg\} + \underbrace{(\tau_{nj}^{x} c_{jt}^{f})^{1-\sigma}}_{\text{Foreign varieties}} .$$

That equation can be rewritten as:

$$
\begin{aligned}
P_{njt}^{1-\sigma} &= \sum_{m\in\mathcal{N}} \Bigg\{ M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma} f(\lambda_{mjt-1}^{T})^{\sigma-1} \frac{\theta}{\tilde{\theta}} \frac{1}{1-\kappa^{-\theta}} (\phi_{mjt}^{min})^{\theta} \\
&\times \Bigg[\Big((\phi_{mjt}^{min})^{-\tilde{\theta}} - (\bar{\phi}_{mjt}^{T})^{-\tilde{\theta}} \Big) + \Big(\frac{\eta}{1-s_{mjt}}\Big)^{\sigma-1} \Big((\bar{\phi}_{mjt}^{T})^{-\tilde{\theta}} - (\phi_{mjt}^{max})^{-\tilde{\theta}} \Big) \Bigg] \Bigg\} + (\tau_{nj}^{x} c_{jt}^{f})^{1-\sigma} \\
&= \sum_{m\in\mathcal{N}} \Bigg\{ M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma} f(\lambda_{mjt-1}^{T})^{\sigma-1} \frac{\theta}{\tilde{\theta}} \frac{1}{1-\kappa^{-\theta}} (\phi_{mjt}^{min})^{\sigma-1} \\
&\times \Bigg[\Big(\Big(\frac{\eta}{1-s_{mjt}}\Big)^{\sigma-1} - 1 \Big) \Big(\frac{\bar{\phi}_{mjt}^{T}}{\phi_{mjt}^{min}} \Big)^{-\tilde{\theta}} + \Big(1 - \Big(\frac{\eta}{1-s_{mjt}}\Big)^{\sigma-1} \kappa^{-\tilde{\theta}} \Big) \Bigg] \Bigg\} + (\tau_{nj}^{x} c_{jt}^{f})^{1-\sigma} \\
&= \sum_{m\in\mathcal{N}} \Bigg\{ M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma} \times \\
& f(\lambda_{mjt-1}^{T})^{\sigma-1} \frac{\theta}{\tilde{\theta}} \frac{1}{1-\kappa^{-\theta}} (\phi_{mjt}^{min})^{\sigma-1} \\
&\times \Bigg[\Big(\Big(\frac{\eta}{1-s_{mjt}}\Big)^{\sigma-1} - 1 \Big) (\tilde{\lambda}_{mjt}^{T})^{\frac{\tilde{\theta}}{\theta}} + \Big(1 - \Big(\frac{\eta}{1-s_{mjt}}\Big)^{\sigma-1} \kappa^{-\tilde{\theta}} \Big) \Bigg] \Bigg\} \\
&+ (\tau_{nj}^{x} c_{jt}^{f})^{1-\sigma},
\end{aligned}
$$

where $\tilde{\theta} = \theta - (\sigma - 1)$ and $\tilde{\lambda}_{njt}^{T}$. The last equality comes from Equation (1.13).

From the algebra above, a price index can be re-expressed as:

$$
P_{njt}^{1-\sigma} = \sum_{m\in\mathcal{N}} \Bigg[M_{mj} \underbrace{(\mu\tau_{mnj}c_{mjt})^{1-\sigma}}_{\text{Unit cost}} \times \underbrace{(\bar{\phi}_{mjt}^{avg})^{\sigma-1}}_{\substack{\text{Average productivity}\\ \text{including subsidies}}} \Bigg] + \underbrace{(\tau_{nj}^{x} c_{jt}^{f})^{1-\sigma}}_{\substack{\text{Consumer foreign}\\ \text{market access}}},
$$

where

$$
\begin{aligned}
\bar{\phi}_{njt}^{avg} &= \bar{\phi}^{avg}(\lambda_{njt-1}^{T}, \lambda_{njt}^{T}, s_{njt}, \phi_{njt}^{min}) \\
&= \frac{\theta f(\lambda_{njt-1}^{T})(\phi_{njt}^{min})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})} \times \Bigg\{ \Big(\Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1} - 1 \Big) (\tilde{\lambda}_{njt}^{T})^{\frac{\tilde{\theta}}{\theta}} \\
&+ \Big(1 - \Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1} \kappa^{-\tilde{\theta}} \Big) \Bigg\},
\end{aligned}
$$

$\tilde{\lambda}_{njt}^{T} = (1-\kappa^{-\theta})\lambda_{njt}^{T} + \kappa^{-\theta}$ and $\tilde{\theta} = \theta - (\sigma-1)$.[6] Price index depend on the three terms: unit cost, average productivity including subsidies $\bar{\phi}_{njt}^{avg}$, and consumer foreign market

[6] When $\lambda_{njt}^{T} \to 0$, the average productivity becomes $\bar{\phi}_{njt}^{avg} = \frac{\theta}{\tilde{\theta}(1-\kappa^{-\theta})} f(\lambda_{njt-1}^{T})(\phi_{njt}^{min})^{\sigma-1}(1-\kappa^{-\tilde{\theta}})$. When $\lambda_{njt}^{T} \to 1$, the average productivity becomes $\bar{\phi}_{njt}^{avg} = \frac{\theta}{\tilde{\theta}(1-\kappa^{-\theta})} f(\lambda_{njt-1}^{T})(\phi_{njt}^{min})^{\sigma-1}\Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1}(1-\kappa^{-\tilde{\theta}})$.

access $(\tau^x_{nj} c^f_{jt})^{1-\sigma}$. $\bar{\phi}^{avg}_{njt}$ captures how region n can produce sector j intermediate varieties at cheaper cost than other regions. Region n can produce at cheaper costs if it has technological advantages (λ^T_{njt}, λ^T_{njt-1}, ϕ^{min}_{njt}) or higher subsidies (s_{njt}). Holding other variables constant, the price index is lower when (i) neighboring regions have lower unit costs (either lower τ_{nmj} or c_{mjt}), (ii) neighboring regions have higher productivity or obtain more subsidies (higher $\bar{\phi}^{avg}_{njt}$), or (iii) the price of imported inputs is lower (lower τ^x_{nj} or c^f_{jt}).

The average productivity including subsidies increases in the share of adopters in the previous period λ^T_{njt-1}, the share of adopters in the current period λ^T_{njt}, subsidies s_{njt}, and the natural advantage captured by the Pareto lower bound ϕ^{min}_{njt}. The share of adopters in $t-1$ increases average productivity directly through spillover and indirectly by inducing more firms to adopt technology in period t (Equation (1.13)). The current share of adopters increases the average productivity through direct productivity gains. Subsidies increase the average productivity directly by lowering the cost of production for adopters and indirectly by inducing more firms to become adopters in t. Finally, a natural advantage is an exogenous productivity shifter.

Gross Output and Export. Region n's sector j gross output R_{njt} is the sum of gross output for domestic expenditures R^d_{njt} and the total value of export R^x_{njt}: $R_{njt} = R^d_{njt} + R^x_{njt}$.

Regional exports can be written as

$$R^x_{njt} = M_{nj}\Bigg[\int_{\bar{\phi}^T_{njt}}^{\bar{\phi}^{max}_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}(1-s_{njt})c_{njt}}{\eta f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) + \int_{\bar{\phi}^x_{njt}}^{\bar{\phi}^T_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}c_{njt}}{f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it})\Bigg] D^f_{jt},$$

where the first and the second terms inside the brackets are the total sum of exports by adopters and non-adopters in sector j of region n.

The first term inside the bracket can be expressed as:

$$\begin{aligned}
&\int_{\bar{\phi}^{T}_{njt}}^{\bar{\phi}^{max}_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^{x}_{nj}s_{njt}c_{njt}}{\eta f(\lambda^{T}_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) \\
&= \frac{\theta f(\lambda^{T}_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}\Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1}(\phi^{min}_{njt})^{-\theta}\Big((\bar{\phi}^{T}_{njt})^{-\tilde{\theta}} - (\kappa\phi^{min}_{njt})^{-\tilde{\theta}}\Big) \\
&= \frac{\theta f(\lambda^{T}_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}\Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1}(\phi^{min}_{njt})^{\sigma-1}\Big((\tilde{\lambda}^{T}_{njt})^{\frac{\tilde{\theta}}{\theta}} - \kappa^{-\tilde{\theta}}\Big),
\end{aligned}$$

where $\tilde{\lambda}^{T}_{njt} = (1-\kappa^{-\theta})\lambda^{T}_{njt} + \kappa^{-\theta}$. The last equality comes from Equation (1.13).

The second term can be re-expressed as:

$$\begin{aligned}
&\int_{\bar{\phi}^{x}_{njt}}^{\bar{\phi}^{T}_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^{x}_{nj}c_{njt}}{f(\lambda^{T}_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) \\
&= \frac{\theta f(\lambda^{T}_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}(\phi^{min}_{njt})^{-\theta}\Big((\bar{\phi}^{x}_{njt})^{-\tilde{\theta}} - (\bar{\phi}^{T}_{njt})^{-\tilde{\theta}}\Big) \\
&= \frac{\theta f(\lambda^{T}_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}(\phi^{min}_{njt})^{\sigma-1}\Big((\tilde{\lambda}^{x}_{njt})^{\frac{\tilde{\theta}}{\theta}} - (\tilde{\lambda}^{T}_{njt})^{\frac{\tilde{\theta}}{\theta}}\Big),
\end{aligned}$$

where $\tilde{\lambda}^{x}_{njt} = (1-\kappa^{-\theta})\lambda^{x}_{njt} + \kappa^{-\theta}$. The last equality comes from the fact that $\lambda^{x}_{njt} = 1 - G_{njt}(\bar{\phi}^{x}_{njt})$.

Regional exports can be expressed as:

$$R^{x}_{njt} = M^{x}_{njt}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg,x}_{njt})^{\sigma-1}}_{\substack{\text{Exporters'}\\ \text{average productivity}\\ \text{including subsidies}}} \times \underbrace{(\tau^{x}_{nj})^{1-\sigma}D^{f}_{jt}}_{\substack{\text{Firm foreign}\\ \text{market access}}},$$

where

$$\begin{aligned}
\bar{\phi}^{avg,x}_{njt} &= \bar{\phi}^{avg,x}(\lambda^{T}_{njt-1}, \lambda^{T}_{njt}, \lambda^{x}_{njt}, s_{njt}, \phi^{min}_{njt}) \\
&= \frac{\theta f(\lambda^{T}_{njt-1})(\phi^{min}_{njt})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}\frac{(\tilde{\lambda}^{x}_{njt})^{\frac{\tilde{\theta}}{\theta}}}{\lambda^{x}_{njt}} \\
&\times \left\{\Big(\Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1} - 1\Big)\Big(\frac{\tilde{\lambda}^{T}_{njt}}{\tilde{\lambda}^{x}_{njt}}\Big)^{\frac{\tilde{\theta}}{\theta}} \right. \\
&\left. + \Big(1 - \Big(\frac{\eta}{1-s_{njt}}\Big)^{\sigma-1}\kappa^{-\tilde{\theta}}(\tilde{\lambda}^{x}_{njt})^{-\frac{\tilde{\theta}}{\theta}}\Big)\right\},
\end{aligned}$$

$\tilde{\lambda}^x_{njt} = (1-\kappa^{-\theta})\lambda^x_{njt} + \kappa^{-\theta}$ and $\bar{\phi}^{avg,x}_{njt}$ represent the exporters' average productivity including subsidies.

Gross output for domestic expenditures and regional exports are written as:

$$R^d_{njt} = M_{nj}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg}_{njt})^{\sigma-1}}_{\substack{\text{Average productivity} \\ \text{including subsidies}}} \times \underbrace{\sum_{m \in \mathcal{N}} \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt}}_{\substack{\text{Firm domestic} \\ \text{market access}}}.$$

and

$$R^x_{njt} = M^x_{njt}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg,x}_{njt})^{\sigma-1}}_{\substack{\text{Exporters'} \\ \text{average productivity} \\ \text{including subsidies}}} \times \underbrace{(\tau^x_{nj})^{1-\sigma} D^f_{jt}}_{\substack{\text{Firm foreign} \\ \text{market access}}}.$$

Average productivity increases for both total domestic sales and export, as do access to markets and subsidies. The cost of production also decreases for domestic sales and exports.

One difference between $\bar{\phi}^{avg,x}_{njt}$ and $\bar{\phi}^{avg}_{njt}$ is that $\bar{\phi}^{avg,x}_{njt}$ also depends on shares of exporters λ^x_{njt}. λ^x_{njt} captures selection induced by fixed export costs. Because of fixed export costs, only more productive firms self-select into exporting, which makes the average productivity of exporters higher than the average productivity of all firms: $\bar{\phi}^{avg,x}_{njt} > \bar{\phi}^{avg}_{njt}$. The average productivity of exporters decreases in shares of exporters λ^x_{njt} because larger shares of exporters implies that less productive firms participate in exporting, which in turn leads to weaker selection effects and lowers the average productivity of exporters. At one extreme where all firms are exporting ($\lambda^x_{njt} = 1$), there is no selection effect and $\bar{\phi}^{avg,x}_{njt}$ becomes equal to $\bar{\phi}^{avg}_{njt}$.

A.3.2 Analytical Results: Multiple Steady States

Derivation of the Equilibrium Share of Adopters in the Simplified Model.

In the simplified model, the cutoff for adoption is expressed as

$$(\bar{\phi}_t^T)^{\sigma-1} = \frac{\sigma P_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma} f(\lambda_{t-1}^T)^{\sigma-1} P_t^{\sigma} Q_t}$$

and the probability of adoption is $\lambda_t^T = (\bar{\phi}_t^T)^{-\theta}$, which can be re-written as

$$(\lambda_t^T)^{-\frac{1}{\theta}} = \bar{\phi}_t^T$$

First, we show that

$$Q_t = \left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T)$$

and

$$\frac{w_t}{P_t} = \frac{\sigma-1}{\sigma}\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T),$$

where $\tilde{\theta} = \theta-(\sigma-1)$. Note that

$$\frac{L_t}{Q_t} = \frac{\int l(\omega)d\omega}{Q_t} = \int \frac{y(\omega)}{Q}\frac{1}{z(\omega)}d\omega = \int \frac{1}{z(\omega)}\left(\frac{p(\omega)}{P_t}\right)^{-\sigma} d\omega,$$

where $z(\omega) = \eta(\omega) f(\lambda_{t-1}^T)\phi(\omega)$ for adopters and $z(\omega) = f(\lambda_{t-1}^T)\phi(\omega)$ for non-adopters. After substituting $L_t = 1$ and $(p(\omega)/P)^{-\sigma} = \frac{\sigma}{\sigma-1}\frac{w_t}{z(\omega)}$ which holds under assumption of monopolistic competition in the above equation, we obtain $Q_t = [\int z(\omega)^{\sigma-1}d\omega]^{\frac{1}{\sigma-1}}$. Using the assumption of Pareto distribution and the cutoff property, we can further derive that

$$\begin{aligned} Q_t = &\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\bar{\phi}_t^T)^{\theta-(\sigma-1)}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T) \\ &= \underbrace{\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}}}_{=A(\lambda_t^T)} \times f(\lambda_{t-1}^T). \end{aligned}$$

Similarly, using

$$P_t = [\mu w_t \int z(\omega)^{\sigma-1} d\omega]^{\frac{1}{1-\sigma}},$$

we can derive that

$$\frac{w_t}{P_t} = \frac{w_t}{[\int (\mu w_t / z_{it}(\omega))^{1-\sigma}]^{\frac{1}{1-\sigma}}} = \frac{\sigma - 1}{\sigma}\left[\frac{\theta}{\tilde{\bar{\theta}}}\Big((\eta^{\sigma-1} - 1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}} + 1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T).$$

From the above equations, we can obtain that

$$\lambda_t^T = \left(\frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} \times A(\lambda_t^T)^{2-\sigma} \times f(\lambda_{t-1}^T)\right)^{\frac{\theta}{\sigma-1}}.$$

Let $\hat{\lambda}_t^T$ be the solution of the above equation. Because the equilibrium share is bounded by 1, the equilibrium share is defined as follows:

$$\lambda_t^T = \begin{cases} \hat{\lambda}_t^T & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T) \frac{\eta^{\sigma-1}-1}{\sigma F^T} < 1 \\ 1 & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T) \frac{\eta^{\sigma-1}-1}{\sigma F^T} \geq 1. \end{cases}$$

Proofs of Proposition I.3: Multiple Steady States

Proof of Proposition I.3(i). We defined equilibrium using the following equation:

$$\lambda_t^T = \left[A(\lambda_t^T)^{2-\sigma} \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} \times f(\lambda_{t-1}^T)\right]^{\frac{\theta}{\sigma-1}}.$$

Because the left hand side strictly increases in λ_t^T but the right hand side strictly decreases in λ_t^T due to Assumption I.2(v), there exists a unique value of λ_t^T that satisfies this equation. If the obtained λ_t^T from this equation is greater than 1, $\lambda_t^T = 1$.

□

Proof of Proposition I.3(ii) and (iii). We prove Proposition I.3(ii) and (iii) using the implicit function theorem. Let

$$G(\lambda_t^T; \eta, \delta, \lambda_{t-1}^T) = A(\lambda_t^T)^{2-\sigma} \times f(\lambda_{t-1}^T) \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} - (\lambda_t^T)^{\frac{\sigma-1}{\theta}}$$

where

$$A(\lambda_t^T) = \left[\frac{\theta}{\theta-(\sigma-1)}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\theta-(\sigma-1)}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} \quad \text{and} \quad f(\lambda_{t-1}^T) = exp(\delta\lambda_{t-1}^T).$$

Note that in period t, firms take $f(\lambda_{t-1}^T)$ as given, so $f(\lambda_{t-1}^T)$ is just a constant in the above equation.

Taking the derivative with respect to λ_t^T, we obtain

$$\frac{\partial G}{\partial \lambda_t^T} = \left(\frac{2-\sigma}{\sigma-1}\right) A(\lambda_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - \frac{\sigma-1}{\theta}(\lambda_t^T)^{\frac{-\theta+(\sigma-1)}{\theta}} < 0,$$

where the last inequality comes from $\sigma > 2$ (Assumption I.2).

Taking the derivative with respect to λ_{t-1}^T, we obtain

$$\frac{\partial G}{\partial \lambda_{t-1}^T} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} exp(\delta\lambda_{t-1}^T)\delta > 0.$$

Applying the implicit function theorem , we obtain

$$\frac{\partial \lambda_t^T}{\partial \lambda_{t-1}^T} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \lambda_{t-1}^T} > 0,$$

which proves that λ_t^T strictly increases in λ_{t-1}^T. This proves Proposition I.3(ii).

Taking the derivative with respect to η, we obtain

$$\begin{aligned}
\frac{\partial G}{\partial \eta} &= \left(\frac{2-\sigma}{\sigma-1}\right) A(\lambda_t^T)^{3-2\sigma} f(\lambda_{t-1}^T)\frac{\theta}{\theta-(\sigma-1)}(\lambda_t^T)^{\frac{\theta-(\sigma-1)}{\theta}}(\sigma-1)\eta^{\sigma-2}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\
&+ A(\lambda_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T} \\
&= A(\lambda_t^T)^{3-2\sigma} f(\lambda_{t-1}^T)\frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T}\frac{\theta}{\theta-(\sigma-1)} \\
&\times \left[\frac{1}{\sigma-1}(\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\theta}{\theta-(\sigma-1)}}+1\right] > 0.
\end{aligned}$$

Taking the derivative with respect to δ, we obtain

$$\frac{\partial G}{\partial \delta} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} exp(\delta\lambda_{t-1}^T)\lambda_{t-1}^T > 0.$$

Applying the implicit function theorem,

$$\frac{\partial \lambda_t^T}{\partial \eta} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \eta} > 0$$

and

$$\frac{\partial \lambda_t^T}{\partial \delta} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \delta} > 0.$$

This proves Proposition I.3(iii). □

Proof of Proposition I.3(iv). First, we show that λ_t^T is strictly convex in λ_{t-1}^T. To show the strict convexity, we have to show that $\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} > 0$. We show this by applying the implicit function theorem and doing some tedious algebra. Applying the implicit function theorem,

$$\begin{aligned}\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} = -\frac{1}{(\partial G/\partial \lambda_t^T)^3} \times \Bigg[& \frac{\partial G}{\partial \lambda_{t-1}^T} \times \left(\frac{\partial G}{\partial \lambda_t^T}\right)^2 \\ & - \left(\frac{\partial^2 G}{\partial \lambda_t^T \partial \lambda_{t-1}^T} + \frac{\partial^2 G}{\partial \lambda_{t-1}^T \partial \lambda_t^T}\right) \times \frac{\partial G}{\partial \lambda_{t-1}^T} \times \frac{\partial G}{\partial \lambda_t^T} + \frac{\partial^2 G}{\partial (\lambda_t^T)^2} \times \left(\frac{\partial G}{\partial \lambda_{t-1}^T}\right)^2 \Bigg].\end{aligned}$$

We examine the sign of each term in the above equation.

$$\frac{\partial^2 G}{\partial (\lambda_{t-1}^T)^2} = A(\lambda_t^T)^{2-\sigma} \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} exp(\delta \lambda_{t-1}^T)\delta^2 > 0.$$

$$\begin{aligned}\frac{\partial^2 G}{\partial \lambda_t^T \partial \lambda_{t-1}^T} = \frac{\partial^2 G}{\partial \lambda_{t-1}^T \partial \lambda_t^T} = & \frac{2-\sigma}{\sigma - 1} A(\lambda_t^T)^{3-2\sigma} \\ & \times \left[\frac{\theta - (\sigma - 1)}{\theta} (\eta^{\sigma-1} - 1)(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}\right] \times exp(\delta \lambda_{t-1}^T)\lambda_{t-1}^T < 0.\end{aligned}$$

$$
\begin{aligned}
\frac{\partial^2 G}{\partial(\lambda_t^T)^2} = \frac{(2-\sigma)(3-\sigma)}{(\sigma-1)^2} A(\lambda_t^T)^{2-2\sigma}) &\left[\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}(\eta^{\sigma-1}-1)\right]^2 \\
&\times exp(\delta\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\
+\frac{\sigma-2}{\theta}A(\lambda_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)&\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}-1} \\
&\times exp(\delta\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\
&\quad + \frac{\sigma-1}{\theta}\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\theta-(\sigma-1)}{\theta}-1} > 0.
\end{aligned}
$$

Using the above equations, we obtain $\frac{\partial^2\lambda_t^T}{\partial(\lambda_{t-1}^T)^2} > 0$, which proves strict convexity.

Because the intercept of λ_t^T-axis is always positive and λ_t^T is strictly increasing and strictly convex in λ_{t-1}^T, the locus defined by $(\lambda_{t-1}^T, \lambda_t^T)$ can intersect with the 45-degree line two times at most.[7] Because $\lambda_t^T(\delta, \eta)$ strictly increases in δ and η, there exists $\underline{\delta}$ and $\underline{\eta}$ such that the 45 degree line and the short-run equilibrium curve meet at $\lambda_{t-1}^T = 1$. Also, by the same logic, there exists $\bar{\delta}$ and $\bar{\eta}$ such that the 45 degree line is tangent to the short-run equilibrium curve. The two lines meet at least twice for $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$.

□

Proof of Proposition I.3(v). The welfare of household is $\frac{w_t+\Pi_t}{P_t}$ where Π_t are the aggregate profits summed across all firms in the economy.[8] This can be expressed as $\frac{w_t}{P_t} + \frac{\Pi_t}{P_t}$. Using the following expression

$$
\frac{\Pi_t}{P_t} = \frac{1}{\sigma}\mu^{1-\sigma}(w_t/P_t)^{1-\sigma}\left[\int_{\omega\in\Omega} z(\omega)^{\sigma-1}d\omega\right]Q_t,
$$

we can derive that the welfare can be expressed as $f(\lambda_{t-1}^T)A(\lambda_t^T)$. The welfare in the steady state is $f(\lambda^{T*})A(\lambda^{T*})$, which strictly increases in λ^{T*}. Therefore, the

[7] The intercept is always positive because of the assumption of unbounded Pareto distribution which guarantees a positive share of adopters at $\lambda_{t-1}^T = 0$.

[8] Note that $L_t = 1$.

equilibrium with a larger mass of adopters Pareto-dominates the equilibrium with a smaller mass of adopters.

$\square$

Source of Dynamic Externality

In this subsection, we use the simplified model to show that dynamic externalities are generated because fixed adoption costs are in units of final goods. We show that when fixed adoption costs are in units of labor, there are no dynamic externalities.

Suppose fixed adoption costs are in units of labor. The cutoff for adoption is defined as

$$(\bar{\phi}_t^T)^{\sigma-1} = \frac{\sigma w_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma} f(\lambda_{t-1}^T)^{\sigma-1} P_t^{\sigma} Q_t},$$

where $P_t F^T$ is replaced with $w_t F^T$. $\frac{w_t}{P_t}$ and Q_t regardless of the fact that fixed adoption costs are in units of labor. We can derive that

$$\lambda_t^T = \Big(\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \times \mu \times A(\lambda_t^T)^{1-\sigma}\Big)^{\frac{\theta}{\sigma-1}}.$$

The equilibrium share of adopters in the above equation shows that the static short-run equilibrium is uniquely determined regardless of values of λ_{t-1}^T. This is because a fixed adoption cost is in units of labor. If there were a higher share of adopters in the previous period, that would increase the overall productivity in t. The increase in productivity would lead to increases in the overall demand for labor. As labor demands increase the equilibrium wage, fixed adoption costs ($w_t F^T$) would become higher. In the equilibrium, increases in fixed adoption costs would exactly cancel out increases in overall productivity, which in turn would mean that the equilibrium share of adopters would not be affected by λ_{t-1}^T.

Temporary Subsidies Can Have Permanent Effects Only When Multiple Steady States Exist

We show that temporary subsidies cannot have permanent effects when multiple steady states do not exist in the simplified model in Section 1.5.5. Suppose temporary subsidies are provided temporarily for periods $t \in \{t_0, \ldots, t_1\}$, where $0 < t_0 < t_1$. Between t_0 and $t_1 < \infty$, adopters are subject to an input subsidy rate $\bar{s} < 1$. Also suppose that the short-run equilibrium curve is not sufficiently nonlinear enough to generate multiple steady states and there is only a unique steady-state. For simplicity, we assume that the economy starts at the original steady state in the initial time period.

Figure A.7 graphically illustrates that temporary subsidies have temporary effects when there is a unique steady state. The solid red locus is the original short-run equilibrium curve without any subsidies. In this economy, the strength of the spillover is not large enough to generate multiple steady states. At t_0, an economy jumps up from the original steady state A to a new point B, which is on the new short-run equilibrium curve when subsidy $\bar{s}$ is permanently provided. Point C is the steady state of this new short-run equilibrium curve. Therefore, between t_0 and t_1, it converges to the new steady state C. However, after the end of the temporary subsidies at t_1, the short-run equilibrium curve moves back to the original short-run equilibrium curve and the economy jumps to D and starts converging to the original steady state A.

Even if there is a unique steady state, there is still room for policy interventions due to externalities. However, these policy interventions have to be provided permanently to have permanent effects. For example, the new steady state in Figure A.7 can have a higher level of welfare than the original steady state, and this new steady state can be sustained when $\bar{s}$ is permanently provided each period. This would be similar to the static setting with externalities. However, these permanent policies are inconsistent with the industrialization pattern in South Korea, where adoption subsidies were only provided from 1973 to 1979.

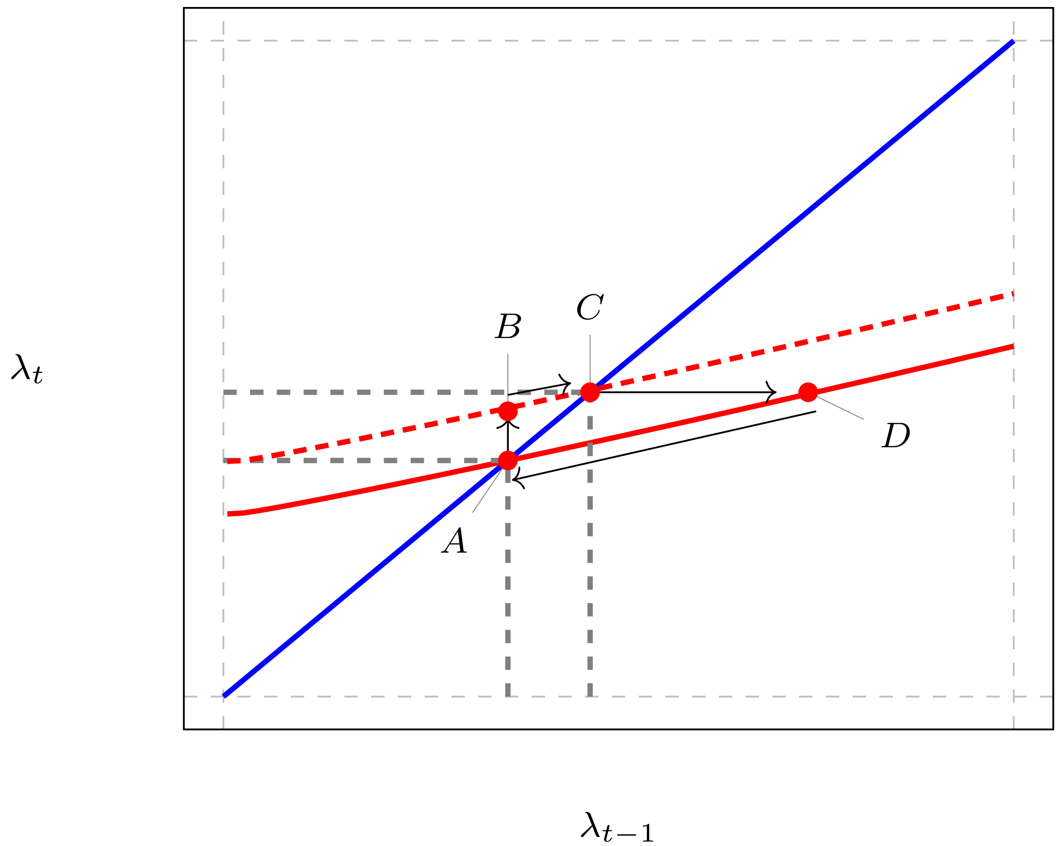


Figure A.7: Temporary Subsidies and No Multiple Steady States.

Notes. This figure illustrates that when multiple steady states do not exist, temporary adoption subsidies cannot have permanent effects. The solid red locus and the dashed red loci are the short-run equilibrium curves when adoption subsidies are not provided and provided permanently, respectively.

A.3.3 Proof of Proposition I.4: Identifying Moment for Subsidies

Proof of Proposition I.4. Suppose that a subsidy plan of the government is given as follows:

$$s_{njt} = \begin{cases} \bar{s} & \text{if} \quad t \in \{2,3\}, \quad \forall n \in \mathcal{N}, \quad \forall j \in \mathcal{J}^T \cap \mathcal{J}^{policy} \\ 0 & \text{otherwise.} \end{cases}$$

Under the assumption that goods are freely traded, sectoral price index and real wage are equalized across regions, that is, $P_{njt} = P_{jt}, \forall n \in \mathcal{N}, \forall j \in \mathcal{J}$. Also, because of the symmetry assumption for $j \in \mathcal{J}^T$, $P_{jt} = P_{j't}$, $D^f_{jt} = D^f_{j't}$, and $F^T_j = F^T_{j'}$ hold for all $j, j' \in \mathcal{J}^T$.[9] These two assumptions in turn imply that firms in sectors where technology adoption is available face the same market size.

Taking log, we can derive the following relationship:

$$\ln \lambda^T_{njt} = \theta\delta\lambda^T_{njt-1} + \underbrace{\frac{\theta}{\sigma-1}\ln\left(\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1} - 1\right)}_{\beta D^{policy}_{jt}}$$
$$\underbrace{-\theta \ln\left(\frac{\mu c_{njt}(\sigma c_{njt}F^T_j)^{\frac{1}{\sigma-1}}}{\left(\sum_{m\in\mathcal{N}} P^{\sigma-1}_{jt}E_{mjt} + D^f_{jt}\right)^{\frac{1}{\sigma-1}}}\right)}_{=\delta_{nt}} + \underbrace{\theta \ln \phi^{min}_{njt}}_{=\epsilon_{njt}},$$

where the second, third, and fourth terms can be mapped to the policy dummy variable D^{policy}_{jt} which equals one if sector j was targeted by the government in period t, region fixed effects δ_{nt}, and the error term ϵ_{njt}.[10] This mapping gives us the following regression model:

$$\ln \lambda^T_{njt} - \theta\delta\lambda^T_{njt-1} = \beta D^{policy}_{jt} + \delta_{nt} + \epsilon_{njt}.$$

The condition for the estimates to be unbiased is $\mathbb{E}[\epsilon_{njt}|D^{policy}_{jt}]$. Under the model

[9] $\gamma^k_j = \gamma^k_{j'}$ and $\gamma^L_j = \gamma^L_{j'}$ for all for all $j, j' \in \mathcal{J}^T$, which leads to $P_{jt} = P_{j't}$ jointly with free trade assumption.

[10] Variation in the third term of the RHS across regions comes from wages w_{nt}. Note that $c_{njt} = (w_{nt}/\alpha^L_j)^{\alpha^L_j}\prod_{k\in\mathcal{J}}(P_{nkt}/\alpha^k_j)^{\alpha^k_j}$.

structure, this is equivalent to $\mathbb{E}[\ln \phi_{njt}^{min} | D_{jt}^{policy}]$. When this condition is satisfied,

$$\hat{\beta} \xrightarrow{p} \beta = \frac{\theta}{\sigma - 1}\left[\ln\left(\left(\frac{\eta}{1-\bar{s}}\right)^{\sigma-1} - 1\right) - \ln(\eta^{\sigma-1} - 1)\right].$$

Given the values of θ, σ, and η, the RHS of the above equation has one-to-one relationship with $\bar{s}$. Therefore , $\bar{s}$ is uniquely identified.

$\square$

A.3.4 Possible Microfoundations for Adoption Spillovers

Local Diffusion of Knowledge

Setup. Consider a closed economy with one sector and N regions. For notational convenience, we omit a subscript j that denotes sectors. Each firm faces a CES demand and is monopolistic for its own variety. Goods are freely tradable across regions.

Firms' Maximization Problem. A firm receives exogenous productivity $\tilde{\phi}_{it}$, which is independent and identically distributed across firms. Given this exogenous productivity, firms make two static decisions each period: (1) whether to adopt advanced foreign technology T_{it}; and (2) a level of innovation a_{it} as in Desmet and Rossi-Hansberg (2014).

Given $\tilde{\phi}_{it}$, a firm optimally chooses (1) whether to adopt technology T_{it} and (2) a level of innovation a_{it}:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}, a_{it}\in[0,\infty)} \left\{ \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}} a_{it}^{\gamma_1}\tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma-1}E_t - T_{it}P_tF^T - w_{nt}a_{it}^{\alpha_1} g(\lambda_{nt-1}^T)B_t \right\},$$

where $T_{it}\in\{0,1\}$ is a dummy variable for adoption status, $\tilde{\eta}$ is direct productivity gains from adoption, w_{nt} are local wages, $P_t^{\sigma-1}E_t$ is market size, F^T is the total fixed adoption cost in units of labor, and $a_{it}^{\alpha_1} g(\lambda_{nt-1}^T)B_t$ is the cost of innovation in units of labor. $\alpha_1 > 0$ holds so that the cost of adoption increases in a_{it}. To simplify the algebra, we assume that B_t is proportional to market size $P_t^{\sigma-1}E_t$; that is, $B_t = b_1 P_t^{\sigma-1}E_t$ with a constant term b_1 .

The positive externalities of adoption come from $g(\lambda_{nt-1}^T)$ of the cost of innovation.

We assume that $\frac{\partial g(\lambda_{nt-1}^{T})}{\partial \lambda_{nt-1}^{T}} < 0$ holds, so a larger share of adopters in the previous period decreases the cost of innovation in the current period. This cost specification captures local diffusion knowledge from newly adopted technologies. With more firms adopting advanced technologies, other local firms are more likely to learn new ideas from these adopters and can use this knowledge for their own innovation. $g(\lambda_{nt-1}^{T})$ captures the local diffusion of ideas in a reduced-form. We assume that $\gamma_1(\sigma-1) - \alpha_1 + 1 < 0$ holds.[11]

A firm's optimal choice of a_{it} is characterized by the following first-order condition:

$$\gamma_1(\sigma-1)a_{it}^{\gamma_1(\sigma-1)}\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}}\tilde{\phi}_{it}}\right)^{1-\sigma} - b_1 w_{nt}\alpha_1 a_{it}^{\alpha_1-1}g(\lambda_{nt-1}^{T}) = 0,$$

which gives the optimal level of own innovation a_{it}^{*}

$$a_{it}^{*} = \bar{C}_{nt}^{1} g(\lambda_{nt-1}^{T})^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}}(\tilde{\eta}^{T_{it}}\tilde{\phi}_{it})^{\frac{1-\sigma}{\alpha_1-1-\gamma_1(\sigma-1)}},$$

where $\bar{C}_{nt}^{1}$ is a collection of constants and variables that are common within region n.[12] Note that both $\frac{\delta_{-1}}{\alpha_1-1-\gamma_1(\sigma-1)} > 0$ and $\frac{1-\sigma}{\alpha_1-1-\gamma_1(\sigma-1)} > 0$ hold. This implies that the optimal amount of innovation increases in a share of adopters in the previous period λ_{nt-1}^{T}, increases if $T_{it} = 1$, and increases in exogeonus productivity $\tilde{\phi}_{it}$. Substituting the optimal a_{it}^{*}, a firm's maximization problem can be rewritten as:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} \left\{\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{(\bar{C}_{nt}^{1})^{\gamma_1} g(\lambda_{nt-1}^{T})^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}}(\tilde{\eta}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}})^{T_{it}}\tilde{\phi}_{it}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}}\right)^{1-\sigma} \times P_t^{\sigma-1}E_t - T_{it}P_t F^{T}\right\}.$$

Note that $g(\lambda_{nt-1}^{T})^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}}$ can be mapped to $f(\lambda_{nt-1}^{T})$, $\tilde{\phi}_{it}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}$ can be mapped to ϕ_{it}, and $\tilde{\eta}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}$ can be mapped to η in Equation (1.10) in the main text.

[11] This parameter restriction guarantees the second-order condition of a firm's maximization problem.

[12] Specifically, $\bar{C}_{nt}^{1} = \left[\frac{\sigma b_1 \alpha_1}{\gamma_1(\sigma-1)}\left(\frac{\sigma}{\sigma-1}\right)^{\sigma-1}\right]^{\frac{1}{\gamma_1(\sigma-1)-\alpha_1+1}} w_{nt}^{\frac{\sigma}{\gamma_1(\sigma-1)-\alpha_1+1}}$.

Historical Case Study. The case study comes from (Kim, 1997, p. 182-184). Wonil Machinery Work (henceforth Wonil) started its business as a small hot and cold rolling mill producer. One local firm imported a more sophisticated 4-high nonreverse cold rolling mill, which was a technology widely used in developed countries. Wonil's engineers had an opportunity to see how the local firm was operating the state of the art mills, and could obtain technical information indirectly from this local firm. From this opportunity, Wonil could develop its own 4-high cold rolling mill blueprints and start producing them without adopting from foreign countries. This development of own blueprints was considered to be a milestone in the firms' history.

Learning Externalities and Labor Mobility in an Imperfect Labor Market

Setup. Consider a closed economy with one sector and N regions. For notational convenience, we omit a subscript j that denotes sectors. Each firm faces a CES demand and is monopolistic for its own variety. Goods are freely tradable across regions.

In each region, there is a unit measure of engineers and firms. Engineers live two periods, child and adult. They only consume and work in their adulthood. They cannot move to new locations. Once engineers become adults in the second period, they give birth to a child. Engineers who work in firms that adopted technologies pass their knowledge to their children. This learning from parents increases the engineering skills of children when they grow up, which increases engineering skills by $\gamma_1 > 1$. If parents do not work in firms with foreign technology, their children's engineering skills are 1. We assume that the engineering skills of newborn children are 1 if the parents work for non-adopter firms and $\gamma_1 > 1$ if the parents work for adopter firms.

Following Acemoglu (1996), we assume that engineers and firms are randomly matched one to one. The surplus this match generates–that is, the profits generated–

is divided among engineers and firms based on Nash bargaining. Managers take a proportion of $\tilde{\beta}$. Once engineers and firms are randomly matched within a region, they jointly maximize profits.

Because the firm makes decisions about adopting technology before the matching happens, it must make these decisions based on anticipated profits. A firm's overall productivity depends on (1) exogenous productivity $\tilde{\phi}_{it}$ that is iid drawn in each period, (2) the engineering skills of matched engineers, and (3) adoption decisions.

Firms' Maximization Problem. Because of the random matching process, firms are matched with engineers with higher engineering skills γ_1 with a probability of λ^T_{nt-1} and they are matched with engineers with lower skills 1 with a probability of $1-\lambda^T_{nt-1}$.

A firm's maximization problem can be written as

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} (1-\tilde{\beta})\Bigg\{ \lambda^T_{nt-1}\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}}\gamma_1\tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma-1}E_t \\ + (1-\lambda^T_{nt-1})\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}}\tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma-1}E_t - P_t F^T T_{it} \Bigg\},$$

where λ_{nt-1} is a local share of adopters in the previous period, $\tilde{\phi}_{it}$ is exogenous productivity, w_{nt} is a local wage, T_{it} is a binary adoption decision, F^T is a fixed adoption cost in units of final goods, γ_1 is engineering skills of engineers whose parents worked in adopter firms, and $\tilde{\eta}$ is the direct productivity gain from adoption. Doing some algebra, the maximization problem above can be rewritten as

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} (1-\tilde{\beta})\left\{ \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{f}(\lambda^T_{nt-1})\tilde{\eta}^{T_{it}}\tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma-1}E_t - P_t F^T T_{it} \right\},$$

where

$$\tilde{f}(\lambda^T_{nt-1}) = [\lambda^T_{nt-1}(\gamma_1^{\sigma-1}-1)+1]^{\frac{1}{\sigma-1}}.$$

$\tilde{f}(\lambda^T_{nt-1})$ increases in the local share of adopters in the previous period, and corresponds to $f(\lambda^T_{njt-1})$ in Equation (1.10) in the main text.

Historical Case Study. In the 1970s, labor mobility across firms was high in South Korea (Kim and Topel, 1995). The average duration of a job in the manufacturing sector in South Korea was around 4 years, which was less than half of the average of a job in the United States (9 years).

Consistent with the aggregate statistics from Kim and Topel (1995), Enos and Park (1988, Chapter 7) provides a historical case study on the diffusion of knowledge through labor mobility in steel industry. The Pohang Iron and Steel Company Ltd. (POSCO), the nation's first integrated steel mill, began operation in 1973. Given South Korea's lack of technology, imported technology played a significant role for POSCO when it began operating. The government heavily subsidized POSCO for the adoption of technology and installation of imported capital equipment associated with the imported technologies. Some of the technicians who left POSCO got jobs in firms located near POSCO that produced capital goods. The technicians helped those firms produce capital equipment that POSCO used, such as equipment for treating water and collecting dust and a large magnetic crane. In the early 1970s, this capital equipment was all imported, but it started to be produced by local suppliers because of knowledge spillover from technicians who had worked at POSCO.

Enos and Park (1988, p. 166) provides another example about the role of labor mobility flows between big firms. Daewoo Heavy Industries Ltd (henceforth Daewoo) built the first diesel engine plant in South Korea after adopting technology from MAN in West Germany. However, one year after Daewoo began operating the plant, Hyundai Heavy Industries (henceforth Hyundai) adopted technology from Perkins in the United States and began producing diesel engines. When it began operations, Hyundai lured skilled engineers who had acquired technological knowledge away from Daewoo by offering them higher salaries. Daewoo lost 33% of its skilled workers as a result.

Both aggregate statistics on labor mobility and two historical case studies support one potential mode of knowledge diffusion through labor mobility.

A.4 Appendix: Reduced-Form

A.4.1 Additional Tables

Table A.3: Descriptive Statistics: Winners vs. Losers Design Samples from the Year of the Cancellation to 5 Years before the Cancellation

	Winner				Loser				t-Statistics
	Mean	Med.	SD	Obs.	Mean	Med.	SD	Obs.	(Col. 1 - Col. 5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log sales	17.80	18.21	2.22	133	18.46	18.45	1.78	131	2.36 [0.13]
log employment	7.34	7.60	1.23	109	7.07	7.19	1.54	130	0.23 [0.64]
log fixed assets	17.15	17.10	2.26	162	17.19	17.64	2.26	158	0.01 [0.93]
log assets	18.00	17.99	2.10	162	18.12	18.40	2.08	158	0.07 [0.80]
log value added/emp	9.57	9.70	1.26	102	9.95	9.62	1.35	122	1.55 [0.22]

Notes. This table reports the descriptive statistics of the winners vs. losers design samples from the year of the cancellation to 5 Years before the cancellation. Column (9) reports the t-statistics of the mean difference between winners and losers with its p value in brackets. Standard errors are two-way clustered by pair and firm and reported in parenthesis. The number of pairs and firms are 34 and 57. All monetary values are measured in 2015 US dollars.

Table A.4: Covariate Balance Test: Winners vs. Losers Design Samples from the Year of the Cancellation to 5 Years before the Cancellation

Dep. Var. $\mathbb{1}[Adopt_{it}]$	Bivariate		Multivariate	
	(1)	(2)	(3)	(4)
log sales	-0.04 (0.03)	-0.1 (0.07)	-0.49 (0.14)***	0.14 (0.47)
N	264	262		
Log employment	0.04 (0.03)	0.05 (0.07)	0.29 (0.15)*	-0.36 (0.5)
N	239	238		
Log fixed assets	0.00 (0.02)	0.02 (0.07)	-0.02 (0.16)	0.16 (0.22)
N	319	319		
Log assets	0.00 (0.02)	0.00 (0.08)	0.22 (0.21)	0.03 (0.33)
N	213	212		
Log labor productivity	-0.06 (0.03)	-0.06 (0.06)	0.27 (0.14)*	-0.36 (0.49)
N	224	221	224	221
F-test [p val]			4.55 [0.00]	0.72 [0.61]
Year FE	✓	✓	✓	✓
Pair FE		✓		✓

Notes. This table reports the covariate balance tests of the winners vs. losers design samples from the year of the cancellation to 5 years before the cancellation. The dependent variable is a dummy variable that equals 1 if a firm adopted technology in the event time. Each cell in columns (1) and (2) reports estimates from a separate bivariate regression. F statistics of joint significance are reported for multivariate regressions, and their p-values are reported in brackets. Standard errors are two-way clustered by pair and firm and reported in parenthesis. This dataset has 33 pairs and 55 firms.

Table A.5: Descriptive Statistics of Patenting Activities by Foreign Contractors: Winners vs. Losers Design Samples

	Winner				Loser				t-Statistics	
	Mean	Med.	SD	Obs.	Mean	Med.	SD	Obs.	(Col. 1 - Col. 5)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
	Panel A. Yearly Measures									
$\ln(\text{Patent} + 1)$	1.54	0.00	2.11	34	1.73	0.00	2.55	34	0.14	[0.71]
$\ln(\text{Citation} + 1)$	1.71	0.00	2.36	34	2.06	0.00	2.88	34	0.34	[0.57]
$\mathbb{1}[\text{Patent} > 0]$	0.44	0.00	0.50	34	0.39	0.00	0.49	34	0.24	[0.63]
$\mathbb{1}[\text{Citation} > 0]$	0.42	0.00	0.50	34	0.42	0.00	0.50	34	0.00	[1.00]
	Panel B. Cumulative Measures									
$\ln(\text{Cum. Patent} + 1)$	2.20	0.00	2.72	34	2.57	1.15	3.13	34	0.35	[0.56]
$\ln(\text{Cum. Citation} + 1)$	2.39	0.00	2.94	34	2.85	1.50	3.41	34	0.46	[0.50]
$\mathbb{1}[\text{Cum. Patent} > 0]$	0.47	0.00	0.51	34	0.56	1.00	0.50	34	0.58	[0.45]
$\mathbb{1}[\text{Cum. Citation} > 0]$	0.47	0.00	0.51	34	0.56	1.00	0.50	34	0.52	[0.48]

Notes. This table reports the descriptive statistics of patenting activites of two groups of foreign firms that made contracts with winners and losers. Column (9) reports t-statistics of the mean difference between two groups with its p-value in brackets. Patent and Citation are the number of patents made in an event year and the number of citations by other patents in an event year. Cum. Patent and Cum. Citation are the cumulative number of patents made up to an event year and the number of citations by other patents up to an event year. Standard errors are clustered by pair and reported in parenthesis.

Table A.6: Local Productivity Spillovers from Technology Adoption: Robustness - 3 Year Lag

Dep. Var.	Log sales					Log revenue TFP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Never-Adopter Sample										
Spill	3.67***	2.96**	4.17***	3.59***	3.23**	2.59*	2.24	2.77*	2.60*	2.11
	(1.25)	(1.40)	(1.43)	(1.20)	(1.55)	(1.41)	(1.43)	(1.45)	(1.36)	(1.43)
ln(Spill-Sales)			–0.02		–0.02			–0.01		–0.01
			(0.02)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.03	–0.02				–0.04**	–0.03
				(0.02)	(0.02)				(0.02)	(0.03)
Adj. R^2	0.18	0.22	0.19	0.19	0.22	0.43	0.41	0.43	0.43	0.41
# clusters (region)	53	53	53	53	53	41	36	41	41	36
# clusters (conglomerate)	636	630	636	636	630	324	275	324	324	275
N	1079	1073	1079	1079	1073	344	292	344	344	292
Panel B: Full Sample										
Spill	3.48***	3.27***	3.67***	3.22***	3.12**	2.67*	2.05	2.63*	2.51*	1.68
	(1.15)	(1.22)	(1.27)	(1.10)	(1.27)	(1.36)	(1.24)	(1.36)	(1.29)	(1.10)
$\mathbb{1}[Adopt]$	0.31**	0.26	0.31**	0.30*	0.24	0.11	0.11	0.11	0.11	0.09
	(0.15)	(0.20)	(0.15)	(0.15)	(0.19)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
ln(Spill-Sales)			–0.01		–0.01			0.00		0.01
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.05***	–0.04*				–0.06***	–0.05**
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.19	0.23	0.19	0.19	0.24	0.36	0.42	0.36	0.37	0.43
# clusters (region)	54	54	54	54	54	45	41	45	45	41
# clusters (conglomerate)	702	697	702	702	697	381	338	381	381	338
N	1264	1259	1264	1264	1259	431	387	431	431	387
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag the adoption status of firms by three years. In Panel A, we use the subsample that include only firms that did not adopt any technology during the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adopters' adoption status. The dependent variables are log sales in columns (1)-(5) and revenue TFP in columns (6)-(10). We estimate revenue TFP based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Local Productivity Spillovers from Technology Adoption: Robustness - 5 Year Lag

Dep. Var.	Log sales					Log revenue TFP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Never-Adopter Sample									
Spill	3.84**	3.48*	4.19**	3.69**	3.63**	4.88***	5.12***	5.03***	4.69***	4.78***
	(1.78)	(1.84)	(1.76)	(1.73)	(1.80)	(1.72)	(1.16)	(1.84)	(1.64)	(1.35)
ln(Spill-Sales)			–0.02		–0.02			–0.01		–0.01
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.03	–0.02				–0.04**	–0.03
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.18	0.22	0.18	0.18	0.22	0.44	0.42	0.44	0.44	0.42
# clusters (region)	53	53	53	53	53	41	36	41	41	36
# clusters (conglomerate)	636	630	636	636	630	324	275	324	324	275
N	1079	1073	1079	1079	1073	344	292	344	344	292
	Panel B: Full Sample									
Spill	4.12***	3.50**	4.28***	3.75***	3.26**	3.86**	3.47*	3.82**	3.53**	2.88
	(1.35)	(1.56)	(1.35)	(1.32)	(1.55)	(1.64)	(2.01)	(1.71)	(1.59)	(1.91)
$\mathbb{1}[Adopt]$	0.32**	0.26	0.32**	0.31*	0.25	0.13	0.13	0.13	0.12	0.11
	(0.16)	(0.20)	(0.16)	(0.16)	(0.20)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)
ln(Spill-Sales)			–0.01		–0.01			0.00		0.00
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.05***	–0.04*				–0.05***	–0.05**
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.19	0.23	0.19	0.19	0.24	0.36	0.42	0.36	0.38	0.43
# clusters (region)	54	54	54	54	54	45	41	45	45	41
# clusters (conglomerate)	702	697	702	702	697	381	338	381	381	338
N	1264	1259	1264	1264	1259	431	387	431	431	387
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by five years. In Panel A, we use the subsample that include only firms that did not adopt any technology during the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adopters' adoption status. The dependent variables are log sales in columns (1)-(5) and revenue TFP in columns (6)-(10). We estimate revenue TFP based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Local Productivity Spillovers from Technology Adoption: Robustness - Spillover Defined at the Broader Level

Dep. Var.	Log sales					Log revenue TFP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Never-Adopter Sample										
Spill	3.54**	3.51**	4.12**	3.36*	3.83**	5.60*	5.37**	5.99*	5.48*	5.24*
	(1.69)	(1.61)	(1.78)	(1.73)	(1.63)	(2.80)	(2.38)	(3.13)	(2.81)	(2.68)
ln(Spill-Sales)			–0.02		–0.02			–0.02		–0.01
			(0.02)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.03*	–0.01				–0.03**	–0.02
				(0.01)	(0.01)				(0.01)	(0.01)
Adj. R^2	0.18	0.21	0.18	0.18	0.22	0.43	0.42	0.44	0.44	0.42
# clusters (region)	38	38	38	38	38	30	27	30	30	27
# clusters (conglomerate)	636	630	636	636	630	324	275	324	324	275
N	1079	1073	1079	1079	1073	344	292	344	344	292
Panel B: Full Sample										
Spill	4.08***	3.36*	4.31***	3.80**	3.23*	5.28*	3.90	5.31*	5.10*	3.58
	(1.40)	(1.74)	(1.55)	(1.43)	(1.81)	(2.71)	(2.88)	(2.86)	(2.65)	(2.78)
$\mathbb{1}[Adopt]$	0.31*	0.24	0.31*	0.30	0.23	0.16	0.13	0.16	0.16	0.12
	(0.18)	(0.22)	(0.18)	(0.18)	(0.22)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
ln(Spill-Sales)			–0.01		–0.01			–0.00		0.01
			(0.01)		(0.01)			(0.02)		(0.01)
ln(Input-MA)				–0.04***	–0.03**				–0.04***	–0.04***
				(0.01)	(0.01)				(0.01)	(0.01)
Adj. R^2	0.19	0.23	0.19	0.19	0.24	0.37	0.42	0.37	0.38	0.43
# clusters (region)	39	39	39	39	39	34	31	34	34	31
# clusters (conglomerate)	702	697	702	702	697	381	338	381	381	338
N	1264	1259	1264	1264	1259	431	387	431	431	387
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

Notes. This table reports the OLS estimates of Equation (1.4). We aggregate regions to 39 regions and construct the spillover measure similar to Equation (1.2) at this broader level. We lag the adoption status of firms by four years. In Panel A, we use the subsample that include only firms that did not adopt any technology during the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adoption status. The dependent variables are log sales in columns (1)-(5) and revenue TFP in columns (6)-(10). We estimate revenue TFP based on Wooldridge (2009). The additional controls ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and for the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at the regiona level defined more broadly and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Local Productivity Spillovers from Technology Adoption: Robustness - Alternative Dependent Variables: Log Employment and Labor Productivity

Dep. Var.	Log employment					Log labor productivity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Never-Adopter Sample									
Spill	4.39***	3.79**	4.94***	4.23***	4.07**	5.55***	5.41***	5.81***	5.34***	5.11**
	(1.54)	(1.64)	(1.70)	(1.50)	(1.76)	(1.84)	(1.62)	(2.08)	(1.78)	(1.92)
ln(Spill-Sales)			–0.02		–0.02			–0.02		–0.01
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.03	–0.02				–0.04**	–0.03
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.18	0.22	0.19	0.19	0.22	0.44	0.42	0.44	0.44	0.42
# clusters (region)	42	39	42	42	39	41	36	41	41	36
# clusters (conglomerate)	351	312	351	351	312	324	275	324	324	275
N	375	335	375	375	335	344	292	344	344	292
	Panel B: Full Sample									
Spill	4.23***	3.93***	4.45***	3.86***	3.72**	4.75***	3.99**	4.72***	4.45***	3.44*
	(1.18)	(1.43)	(1.31)	(1.19)	(1.52)	(1.63)	(1.90)	(1.73)	(1.58)	(1.82)
$\mathbb{1}[Adopt]$	0.32**	0.26	0.32**	0.31**	0.25	0.15*	0.14	0.15*	0.14	0.12
	(0.15)	(0.20)	(0.15)	(0.15)	(0.19)	(0.09)	(0.10)	(0.09)	(0.09)	(0.10)
ln(Spill-Sales)			–0.01		–0.01			0.00		0.00
			(0.01)		(0.01)			(0.02)		(0.02)
ln(Input-MA)				–0.05***	–0.04*				–0.05***	–0.05**
				(0.02)	(0.02)				(0.02)	(0.02)
Adj. R^2	0.19	0.24	0.19	0.19	0.24	0.37	0.43	0.37	0.38	0.43
# clusters (region)	54	54	54	54	54	45	41	45	45	41
# clusters (conglomerate)	411	375	411	411	375	381	338	381	381	338
N	466	430	466	466	430	431	387	431	431	387
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by four years. In Panel A, we use the subsample that include only firms that did not adopt any technology during the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adopters' adoption status. The dependent variables are log employment in columns (1)-(5) and labor productivity in (6)-(10). Labor productivity is defined as value added per worker. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Local Productivity Spillover from Technology Adoption: Robustness - Alternative Dependent Variables: Log Fixed Assets and Assets

Dep. Var.	Log fixed assets					Log assets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Never-Adopter Sample										
Spill	4.55**	5.39***	5.73***	4.51**	6.49***	3.88**	4.08***	4.64**	3.81**	4.70***
	(2.10)	(1.86)	(2.08)	(2.10)	(1.83)	(1.62)	(1.51)	(1.75)	(1.61)	(1.64)
ln(Spill-Sales)			–0.04***		–0.04**			–0.03**		–0.03*
			(0.01)		(0.02)			(0.01)		(0.01)
ln(Input-MA)				–0.01	0.00				–0.01	–0.00
				(0.02)	(0.03)				(0.02)	(0.02)
Adj. R^2	0.12	0.18	0.13	0.12	0.19	0.10	0.17	0.11	0.10	0.17
# clusters (region)	53	53	53	53	53	53	53	53	53	53
# clusters (conglomerate)	631	625	631	631	625	635	629	635	635	629
N	1072	1066	1072	1072	1066	1078	1072	1078	1078	1072
Panel B: Full Sample										
Spill	3.05**	4.13***	3.68***	2.93**	4.63***	2.88**	3.27***	3.26**	2.69**	3.39**
	(1.41)	(1.18)	(1.36)	(1.41)	(1.18)	(1.20)	(1.21)	(1.31)	(1.19)	(1.29)
$\mathbb{1}[Adopt]$	0.50***	0.39**	0.50***	0.49***	0.39**	0.38***	0.34**	0.38***	0.37***	0.33**
	(0.13)	(0.17)	(0.13)	(0.13)	(0.17)	(0.12)	(0.15)	(0.12)	(0.12)	(0.15)
ln(Spill-Sales)			–0.03**		–0.03*			–0.02		–0.01
			(0.01)		(0.01)			(0.01)		(0.01)
ln(Input-MA)				–0.02	–0.01				–0.02	–0.02
				(0.02)	(0.02)				(0.01)	(0.02)
Adj. R^2	0.15	0.22	0.16	0.15	0.23	0.15	0.20	0.15	0.15	0.20
# clusters (region)	54	54	54	54	54	54	54	54	54	54
# clusters (conglomerate)	696	691	696	696	691	701	696	701	701	696
N	1254	1249	1254	1254	1249	1263	1258	1263	1263	1258
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓

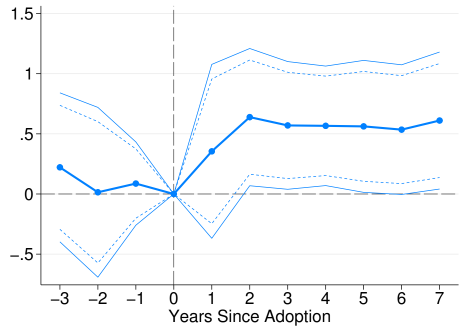
Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by four years. In Panel A, we use the subsample that include only firms that did not adopt any technology until the end of the sample period. In Panel B, we use the full sample including both adopters and non-adopters and control for adopters' adoption status. Dependent variables are log fixed assets in columns (1)-(5) and assets in columns (6)-(10). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Local Productivity Spillovers from Technology Adoption: Robustness - Input Market Access

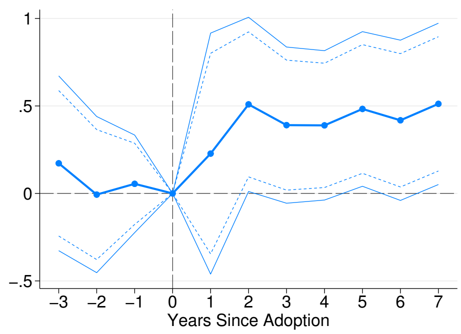
Dep. Var.	Log sales		Log revenue TFP	
	(1)	(2)	(3)	(4)
	Panel A: Never-Adopter Sample			
Spill	4.15***	3.97**	5.36***	5.32***
	(1.49)	(1.73)	(1.79)	(1.87)
ln(Spill-Sales)	–0.02	–0.01	–0.03**	–0.02
	(0.01)	(0.01)	(0.01)	(0.02)
ln(Input-MA)		–0.02		–0.01
(Weight: $1/dist^{1.1}$)		(0.01)		(0.02)
Adj. R^2	0.19	0.22	0.44	0.42
# clusters (region)	53	53	41	36
# clusters (conglomerate)	638	631	326	277
N	1079	1072	346	294
	Panel B: Full Sample			
Spill	3.69***	3.57**	4.51***	3.49*
	(1.18)	(1.48)	(1.57)	(1.91)
$\mathbb{1}[Adopt]$	0.31**	0.25	0.15	0.13
	(0.16)	(0.20)	(0.09)	(0.10)
ln(Spill-Sales)	–0.03**	–0.03*	–0.04***	–0.03**
	(0.01)	(0.01)	(0.01)	(0.02)
ln(Input-MA)		–0.01		0.01
(Weight: $1/dist^{1.1}$)		(0.01)		(0.02)
Adj. R^2	0.19	0.24	0.38	0.43
# clusters (region)	54	54	45	41
# clusters (conglomerate)	704	699	382	339
N	1263	1258	432	388
Region-Sector FE	✓	✓	✓	✓
Conglomerate FE		✓		✓

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by four years. In Panel A, we use the subsample that include only firms that did not adopt any technology until the end of the sample period. In Panel B, we use the full sample of adopters and non-adopters and control for adopters' adoption status. The dependent variables are log sales in columns (1)-(2) and revenue TFP in columns (3)-(4). We estimate revenue TFP based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

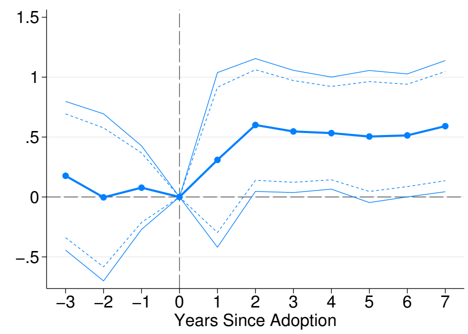
A.4.2 Additional Figures



A. Log revenue TFP based on ACF (2015)



B. Log revenue TFP based on LP (2003)



C. Log revenue TFP based on OLS

Figure A.8: Robustness Checks for Direct Productivity Gains of Technology Adoption: Winners vs. Losers Research Design - Alternative TFP Measures

Notes. This figure illustrates the estimated β_τ^{diff} in Equation (1.1) based on winners vs. losers research design. The dependent variables are log revenue TFP. In Panels A, B, and C, we estimate revenue TFPs based on Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS, respectively. We normalize β_0^{diff} to zero. All specifications control for event time dummies, and firm, pair, and calendar year fixed effects. The figure reports 90 and 95 percent confidence intervals based on standard errors two-way clustered at the levels of pairs and firms.

A.4.3 Empirical Evidence on Winners' Exports

In this section, we provide empirical evidence that winners were more likely to become an exporter and to export more than losers. We merge the pairs of winners and losers with KIS-VALUE that covers firms' exports data after 1980. Because KIS-VALUE coverage is smaller than our firm balance sheet data, some pairs were dropped while merging with KIS-VALUE. 23 out of 34 pairs could be merged with KIS-VALUE.

We pool the sample of matched firms' exports observed 7 or 8 years after the cancellation occurred, which we label as 7-year and 8-year samples, respectively. Then using these 7-year and 8-year samples, we estimate the following pooled OLS regression model:

$$y_{ip,t(p)+\tau} = \beta^{export} \times \mathbb{1}[Adopt_{ip,t(p)}] + \delta_{p\tau} + \epsilon_{ip,t(p)+\tau},$$

where i denotes firm, p pair, and $t(p)$ year in which the event happened for pair p. τ denotes years after the event. $\mathbb{1}[Adopt_{ip,t(p)}]$ is a dummy variable which equals 1 if firm i adopted technology at the time of the event. Dependent variables are $\mathbb{1}[\text{Export}_{ip\tau}]$, $asinh(\text{Export}_{ip\tau})$, and $\ln(\text{Export}_{ip\tau}+1)$. $\mathbb{1}[\text{Export}_{ip\tau}]$ is a dummy variable of firms' adoption status. $asinh(\text{Export}_{ip\tau})$ is the inverse hyperbolic sine transformation of exports. We use the inverse hyperbolic sine transformation to deal with zero exports, so $asinh(\text{Export}_{ip\tau})$ captures both intensive and extensive margins of exports (Burbidge et al., 1988). $\ln(\text{Export}_{ip\tau}+1)$ is log one plus exports. $\delta_{p\tau}$ is pair and τ specific fixed effects. $\epsilon_{ip\tau}$ is the error term. We cluster standard errors at the pair level.

Because we are controlling for $\delta_{p\tau}$, β^{export} is identified by variation within pair. If $\mathbb{1}[Adopt_{ip,t(p)}]$ is uncorrelated with the error term, the estimates admit causal interpretation. Because the sample period of KIS-VALUE begins in 1980, we cannot check pre-trends of exports as in Equation (1.1). Although we cannot check pre-trends for exports, the fact we do not find pre-trends in sales or revenue TFP measures supports that $\mathbb{1}[Adopt_{ip,t(p)}]$ is uncorrelated with the error term.

Table A.12 reports the results. In column (1), the dependent variable is a dummy variable of firms' adoption status. We pool the 7-year and 8-year samples. The estimated coefficient is positive and statistically significant. We find that the adoption increased firms' probability of exporting by 29 percentage points. In columns (2) and (3), we only use the 7-year and 8-year samples, respectively. The estimates remain statistically significant and similar to those in column (1). In columns (4)-(6), the dependent variable is $asinh(\text{Export}_{ip,t(p)+\tau})$. The coefficients are statistically significant and positive, and their magnitude implies that the adoption increased a 0.55 standard deviation of $asinh(\text{Export}_{ip,t(p)+\tau})$. In columns (7)-(9), the dependent variable is $\ln(\text{Export}_{ip,t(p)+\tau} + 1)$. The magnitude of the estimates is similar to those in columns (4)-(6).

Given the small number of clusters, we report the p-values based on the wild cluster bootstrap-t method of Cameron et al. (2008) in the bracket (p-val (CGM)). Using the wild cluster bootstrap-t, the estimates remain statistically significant across all specifications.

Table A.12: Technology Adoption Increased Firms' Exports: Winners vs. Losers Research Design

Dep. Var.	$\mathbb{1}$[Export]			$asinh$(Export)			ln(Export + 1)		
Years after the event (τ)	$\tau = 7, 8$	$\tau = 7$	$\tau = 8$	$\tau = 7, 8$	$\tau = 7$	$\tau = 8$	$\tau = 7, 8$	$\tau = 7$	$\tau = 8$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adopt	0.29**	0.26*	0.32**	5.25**	4.75*	5.79**	5.05**	4.57*	5.56**
	(0.13)	(0.13)	(0.14)	(2.40)	(2.49)	(2.60)	(2.31)	(2.41)	(2.50)
p-val (CGM)	[0.06]	[0.04]	[0.01]	[0.04]	[0.08]	[0.04]	[0.04]	[0.08]	[0.04]
Pair-τ FE	✓			✓			✓		
Pair FE		✓	✓		✓	✓		✓	✓
Adj. R^2	0.20	0.24	0.14	0.24	0.24	0.21	0.24	0.24	0.22
# cluster (pair)	23	23	22	23	23	22	23	23	22
N	90	46	44	90	46	44	90	46	44

Notes. This table reports the estimates of $\mathbb{1}[\text{Adopt}_{ip,t(p)}]$. Robust standard errors in parenthesis are two-way clustered at the region and firm levels. P-values based on the wild cluster bootstrap-t method of Cameron et al. (2008) are reported in the bracket (p-val (CGM)). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4.4 Comparison between the Winners vs. Losers Research Design and the Naive Event Study Design

In this subsection, we compare our estimates from the winners vs. losers research design to estimates based on the following standard two-way fixed effects event-study specification:

$$y_{it} = \sum_{\tau=-3}^{\tau=7} \beta_\tau \times \mathbb{1}[\text{Adopt}_{it}^{\tau}] + \mathbf{X}_{it}'\boldsymbol{\gamma} + \delta_i + \delta_t + \epsilon_{it},$$

where $\mathbb{1}[\text{Adopt}_{it}^{\tau}]$ are event-study variables defined as $\mathbb{1}[\text{Adopt}_{it}^{\tau}] := \mathbb{1}[t - \tau = t(i)]$ and $t(i)$ is year in which firm i adopted technology from foreign firms for the first time. Dependent variables y_{ipt} are log sales, log revenue TFP estimated, and labor productivity defined as value added per worker. δ_i and δ_t are firm and calendar year fixed effects. ϵ_{it} is the error term. We additionally control for observables $\mathbf{X}_{it}$ depending on specifications. We two-way cluster standard errors at the region and firm levels.

Unlike the specification in Equation (1.1) based on the winners vs. losers research design, the above specification uses the full sample. However, the above specification can be problematic for two reasons. First, technology adoption decisions are endogenous, which can make $\mathbb{1}[\text{Adopt}_{it}^{\tau}]$ be correlated with the error term. This endogeneity problem will result in biased estimates for the true impact of technology adoption. Second, because this specification uses pre-treated firms as control groups, it is less robust to problems related to staggered diff-in-diffs design.

Table A.13 reports the results. In columns (1)-(4), the dependent variable is log sales. Across different specifications, we find positive correlation between technology adoption and log sales. Also, there are no pre-trends. However, the magnitude of the estimated coefficients is smaller than those from the winners vs. losers research design. The magnitude becomes smaller, and the coefficients are less precisely estimated once we control additional fixed effects in columns (2)-(4). We observe a similar pattern in columns (5)-(12), where we use log revenue TFP and log labor productivity as dependent variables. For log revenue TFP and log labor productivity, we also find that the magnitude of the estimated coefficients is smaller than those from the winners vs. losers research design.

Suppose the identifying assumption of the winners vs. losers research design holds. Then, the estimates from the naive event study design are downward biased. One potential scenario for this bias is that the government selectively approved technology adoption contracts or provided subsidies for the adoption based on political connections rather than productivity. If less productive firms that are more politically connected were targeted by the government, this might result in the downward bias of the estimates. However, the winners vs. losers research design can deal with this bias induced by the subsidies or political connections. From the fact that both winners and losers got approvals from the government, we can indirectly infer that the two groups had a similar level of political favors. Kim et al. (2021) finds that South Korea's industrial policy increased the degree of misallocation among heavy manufacturing firms, which is consistent with the downward bias. Although the misallocation effects are not the focus of this paper, with these potential misallocation effects of the subsidies, the welfare effects of our quantitative analysis should be interpreted as the upper bound.

Table A.13: Event Study Estimates of Direct Productivity Gains to Adopters: Standard Two-Way Fixed Effects Event-Study Design

Dep. Var.	Log sales				Log revenue TFP				Log labor productivity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
3 years before event	–0.10	–0.07	–0.08	–0.06	–0.04	–0.05	–0.04	–0.03	0.04	0.01	0.03	0.06
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.06)	(0.09)
2 years before event	–0.02	–0.00	–0.00	0.02	0.02	0.02	0.03	0.04	0.05	0.04	0.05	0.06
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
1 year before event	–0.01	0.00	–0.01	0.01	0.06	0.06	0.06*	0.06	0.06	0.05	0.04	0.07
	(0.07)	(0.06)	(0.06)	(0.06)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
Year of event												
1 year after event	0.05	0.03	0.04	0.10*	0.05	0.04	0.04	0.06	0.11	0.10	0.10	0.14*
	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
2 years after event	0.18**	0.15**	0.13*	0.18**	0.15*	0.13	0.14*	0.15	0.19**	0.18**	0.18**	0.18**
	(0.07)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.08)	(0.09)
3 years after event	0.20**	0.17**	0.11	0.16*	0.18**	0.14*	0.16*	0.13	0.25***	0.23***	0.25***	0.23**
	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.09)	(0.10)
4 years after event	0.21**	0.15*	0.08	0.15	0.15	0.08	0.07	0.07	0.19*	0.15	0.15	0.15
	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)	(0.10)	(0.10)	(0.12)	(0.10)	(0.10)	(0.10)	(0.11)
5 years after event	0.27**	0.21*	0.14	0.16	0.20	0.13	0.12	0.07	0.18	0.14	0.16	0.11
	(0.11)	(0.11)	(0.11)	(0.13)	(0.13)	(0.12)	(0.13)	(0.15)	(0.12)	(0.12)	(0.13)	(0.15)
6 years after event	0.31***	0.26***	0.16*	0.21**	0.23**	0.16*	0.13	0.12	0.20	0.16	0.15	0.14
	(0.10)	(0.09)	(0.09)	(0.09)	(0.11)	(0.09)	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)	(0.12)
7 years after event	0.32***	0.25***	0.16	0.20**	0.24**	0.14	0.15	0.11	0.21	0.16	0.20	0.15
	(0.10)	(0.08)	(0.09)	(0.08)	(0.11)	(0.09)	(0.10)	(0.10)	(0.15)	(0.13)	(0.15)	(0.14)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓				✓				✓			
Sector-Year FE		✓	✓			✓	✓			✓	✓	
Region-Year FE			✓				✓				✓	
Region-Sector-Year FE				✓				✓				✓
Adj. R^2	0.83	0.83	0.83	0.83	0.87	0.87	0.86	0.86	0.53	0.54	0.52	0.50
# clusters (region)	59	59	59	59	59	59	58	58	59	59	58	58
# clusters (firm)	3366	3366	3365	3323	2163	2163	2147	2105	2170	2170	2154	2112
N	15955	15955	15915	15639	9216	9216	9136	8923	9242	9242	9162	8950

Notes. This table reports the estimated event study coefficients $\mathbb{1}[\text{Adopt}_{it}^{\tau}]$. $\mathbb{1}[\text{Adopt}_{it}^{0}]$ is normalized to zero. The dependent variables are log sales, log revenue TFP, and log labor productivity defined as value added divided by employment. Value added is obtained as sales multiplied by the value added shares obtained from input-output tables corresponding to each year. We estimate log revenue TFP based on Wooldridge (2009). Robust standard errors in parenthesis are two-way clustered at the region and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4.5 Cross-Sector Spillover

This section provides additional empirical results on cross-sector spillover effects. We augment Equation (1.4) with the cross-spillover measures as follows:

$$\triangle y_{injt} = \beta^S \triangle \text{Spill}_{inj(t-4)} + \sum_{g \neq j} \beta^S_{gj} \triangle \text{Spill}_{ing(t-4)} + \gamma y_{injt_0} + \mathbf{X}'_{injt_0}\boldsymbol{\beta} + \triangle \delta_{njt} + \triangle \epsilon_{injt},$$

where β^S_{gj} captures the cross-sector spillover effect from sectors g to j.

A problem of Equation (1.4) is that there are too many parameters to be estimated given the data. There are $|\mathcal{J}| \times (|\mathcal{J}| - 1)$ of cross-sector spillover parameters. Following Ellison et al. (2010) and Hanlon and Miscio (2017), we parametrize β^S_{gj} using the input-output tables of 1970:

$$\beta^S_{gj} = \beta^S_{for} \gamma^g_j + \beta^S_{back} \gamma^j_g$$

where γ^g_j represents shares of sector g intermediate inputs used by sector j obtained from the input-output table. β^S_{for} and β^S_{back} capture spillover effects through forward and backward linkages, respectively. After substituting the above expression, we can derive the following regression model:

$$\begin{aligned}\triangle y_{injt} = \beta^S \triangle \text{Spill}_{inj(t-4)} \\ + \beta^S_{for} \left(\sum_{g \neq j} \gamma^g_j \triangle \text{Spill}_{ing(t-4)} \right) + \beta^S_{back} \left(\sum_{g \neq j} \gamma^j_g \triangle \text{Spill}_{ing(t-4)} \right) \\ + \gamma y_{injt_0} + \mathbf{X}'_{injt_0}\boldsymbol{\beta} + \triangle \delta_{njt} + \triangle \epsilon_{injt}.\end{aligned}$$

The cross-sector spillover is governed by only two parameters β^S_{for} and β^S_{back}.

Table A.14 reports the OLS estimates for β^S, β^S_{for}, and β^S_{back}. In Panels A and B, we separately control the forward and backward linkage spillovers, respectively. In Panel C, we jointly control them. Across different specifications, we do not find statistically significant results for the cross-sector spillovers. The statistically insignificant results may come from the fact that our sector classification is defined at the broad level.

Table A.14: Cross-Sector Local Productivity Spillovers from Technology Adoption

Dep. Var.	Log sales					Log revenue TFP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Forward Linkage Spillovers									
Spill	4.19**	3.64**	4.68**	4.10**	3.94**	5.98***	5.67***	6.26***	5.79***	5.44***
	(1.64)	(1.65)	(1.75)	(1.59)	(1.73)	(1.95)	(1.71)	(2.13)	(1.90)	(1.89)
Forward Spill (β^S_{for})	–1.71	–1.52	–1.17	–1.36	–0.93	–1.54	–2.86***	–1.23	–1.81	–2.89***
	(1.29)	(1.55)	(1.45)	(1.20)	(1.55)	(2.23)	(0.58)	(2.22)	(2.09)	(0.65)
Adj. R^2	0.18	0.22	0.19	0.18	0.22	0.43	0.42	0.44	0.44	0.42
	Panel B: Backward Linkage Spillovers									
Spill	4.10**	3.57**	4.60**	4.02**	3.87**	5.88***	5.50***	6.17***	5.66***	5.28***
	(1.69)	(1.70)	(1.82)	(1.65)	(1.78)	(1.88)	(1.64)	(2.10)	(1.82)	(1.86)
Backward Spill (β^S_{back})	–7.47	–8.35	–5.56	–7.00	–6.87	–3.47	–8.45	–3.20	–4.63	–9.28
	(6.03)	(5.78)	(7.26)	(6.14)	(6.29)	(7.78)	(5.41)	(8.33)	(7.28)	(5.50)
Adj. R^2	0.18	0.22	0.19	0.19	0.22	0.43	0.42	0.44	0.44	0.42
	Panel C: Forward & Backward Linkage Spillovers									
Spill	4.11**	3.56**	4.61**	4.01**	3.85**	5.94***	5.60***	6.21***	5.72***	5.36***
	(1.73)	(1.71)	(1.85)	(1.68)	(1.80)	(2.03)	(1.76)	(2.22)	(1.97)	(1.94)
Forward Spill (β^S_{for})	–0.35	0.32	–0.05	0.21	0.98	–1.16	–1.69	–0.75	–1.13	–1.43
	(2.65)	(1.99)	(2.79)	(2.54)	(2.03)	(3.22)	(1.87)	(3.02)	(3.19)	(1.79)
Backward Spill (β^S_{back})	–6.58	–9.23	–5.42	–7.54	–9.52	–1.58	–5.37	–1.97	–2.77	–6.69
	(11.38)	(7.78)	(12.60)	(11.25)	(8.42)	(10.77)	(8.27)	(11.06)	(10.37)	(8.26)
Adj. R^2	0.18	0.22	0.19	0.18	0.22	0.43	0.42	0.43	0.44	0.42
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓
ln(Spill-Sales)			✓		✓			✓		✓
ln(Input-MA)				✓	✓				✓	✓
# clusters (region)	53	53	53	53	53	41	36	41	41	36
# clusters (conglomerate)	636	630	636	636	630	324	275	324	324	275
N	1079	1073	1079	1079	1073	344	292	344	344	292

Notes. This table reports the OLS estimates. When we construct the spillover measure defined in Equation (1.2), we lag the adoption status of firms by four years. We use the subsample that include only firms that did not adopt any technology during the sample period. The dependent variables are log sales in columns (1)-(5) and revenue TFP in columns (6)-(10). We estimate revenue TFP based on Wooldridge (2009). The additional controls ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and for the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4.6 Empirical Evidence on Dynamic Complementarity

In this subsection, we provide empirical evidence on the dynamic complementarity. We find that firms that are located closer to neighboring adopters were more likely to adopt technology from foreign firms.

We run the same regression in Equation (1.4) with different dependent variables using the full sample. The number of the sample is larger than that of Panel B of Table 1.2 because of missing values of balance sheet variables whereas we can observe firms' adoption activities every year without missing values. We use two different variables: $\mathbb{1}[\text{New Contract}_{injt}]$ and $asinh(\#\ \text{New Contract}_{injt})$. $\mathbb{1}[\text{New Contract}_{injt}]$ is a dummy variable of whether a firm makes a new technology adoption contract with foreign firms. $asinh(\#\ \text{New Contract}_{injt})$ is the inverse hyperbolic sine transformation of the number of new technology adoption contracts. We use the inverse hyperbolic sine transformation to deal with zero contracts (Burbidge et al., 1988). $asinh(\#\ \text{New Contract}_{injt})$ captures both intensive and extensive margins of new contracts.

$\mathbb{1}[\text{New Contract}_{injt}]$ differs from $\mathbb{1}[Adopt_{injt}]$ which is used to construct the spillover measure in Equation (1.2). $\mathbb{1}[Adopt_{injt}]$ is a dummy variable of whether firm i ever adopted technology at time t. On the other hand, $\mathbb{1}[\text{New Contract}_{injt}]$ is a dummy variable of whether firm i makes a new contract in t. For example, if a firm i is a non-adopter and makes a new contract in time t, both $\mathbb{1}[\text{New Contract}_{injt}]$ and $\mathbb{1}[Adopt_{injt}]$ take the value of 1 in t. If a firm i has made a contract before t but did not make a new contract in t, then only $\mathbb{1}[Adopt_{injt}]$ takes value of 1.

Table A.15 reports the results. In columns (1)-(5), the dependent variables are $\mathbb{1}[\text{New Contract}_{injt}]$. Across the specifications, the estimated coefficients are statistically significant and are positive. One standard deviation increase of the adoption spillover measure increases a firm's probability of making new technology adoption contracts by 1.2 percentage points.[13] With the structural interpretation of the spillover measure, an increase of a one percentage point of the probability of interacting with local adopters increases the probability of making a new contract by a 0.37 percentage point. In columns (5)-(10), the dependent variables are the inverse hyperbolic sine transformation of the number of new contracts. The estimated coefficients imply that one standard deviation increase of the spillover measure increases a 0.28 standard deviation of $asinh$(# New Contract$_{injt}$).[14]

In Tables A.16 and A.17, we conduct the robustness checks with the spillover measure with different lags. When we use the spillover measure lagged by 3 years, the estimated coefficients are statistically significant and positive and stay within one standard error of the coefficients in Table A.15. On the other hand, when we use the spillover measure lagged by 5 years, the estimated coefficients are positive but not statistically significant.

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[13] This is obtained as $1.2 = 100 \times 0.37 \times 0.033$, where 0.37 is the estimated coefficient, and 0.033 is the standard deviation of the spillover measure.

[14] 0.28 is calculated as $0.033 \times 0.45/0.16$, where 0.33 is the standard deviation of the spillover measure, 0.45 is the estimated coefficient, and 0.16 is the standard deviation of $asinh$(# New Contract$_{injt}$).

Table A.15: Dynamic Complementarity in Firms' Technology Adoption Decisions

Dep. Var.	𝟙[New Contract]					$asinh$(# New Contract)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spill	0.35**	0.37***	0.35**	0.35**	0.37***	0.45**	0.46**	0.44**	0.44**	0.46**
	(0.16)	(0.13)	(0.16)	(0.16)	(0.13)	(0.20)	(0.22)	(0.20)	(0.20)	(0.22)
ln(Spill-Sales)			0.00		–0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)
ln(Input-MA)				–0.00	–0.00				–0.00	–0.00
				(0.00)	(0.00)				(0.00)	(0.00)
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓
Adj. R^2	0.15	0.21	0.15	0.15	0.21	0.16	0.27	0.16	0.16	0.27
# cluster (region)	60	60	60	60	60	60	60	60	60	60
# cluster (conglomerate)	1423	1422	1423	1423	1422	1423	1422	1423	1423	1422
N	2706	2705	2706	2706	2705	2706	2705	2706	2706	2705

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by four years. In columns (1)-(5), the dependent variables are a dummy variable of whether a firm makes a new technology adoption contracts made in a given year. In columns (6)-(11), the dependent variables are the inverse hyperbolic sine transformation of the number of new technology adoption contracts made in a given year. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Dynamic Complementarity in Firms' Technology Adoption Decisions: Robustness - 3 Year Lag

Dep. Var.	𝟙[New Contract]					$asinh$(# New Contract)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spill	0.42***	0.38***	0.42***	0.42***	0.39***	0.58**	0.52**	0.58**	0.58**	0.52**
	(0.15)	(0.12)	(0.16)	(0.15)	(0.13)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
ln(Spill-Sales)			0.00		–0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)
ln(Input-MA)				–0.00	–0.00				–0.00	–0.00
				(0.00)	(0.00)				(0.00)	(0.00)
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓
Adj. R^2	0.15	0.21	0.15	0.15	0.21	0.17	0.27	0.17	0.17	0.27
# cluster (region)	60	60	60	60	60	60	60	60	60	60
# cluster (conglomerate)	1423	1422	1423	1423	1422	1423	1422	1423	1423	1422
N	2706	2705	2706	2706	2705	2706	2705	2706	2706	2705

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by three years. In columns (1)-(5), the dependent variables are a dummy variable of whether a firm makes a new technology adoption contracts made in a given year. In columns (6)-(11), the dependent variables are the inverse hyperbolic sine transformation of the number of new technology adoption contracts made in a given year. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Dynamic Complementarity in Firms' Technology Adoption Decisions - Robustness: 5 Year Lag

Dep. Var.	$\mathbb{1}$[New Contract]					*asinh*(# New Contract)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Spill	0.15	0.18	0.15	0.15	0.18	0.18	0.22	0.18	0.18	0.21
	(0.19)	(0.14)	(0.18)	(0.19)	(0.14)	(0.17)	(0.15)	(0.17)	(0.17)	(0.15)
ln(Spill-Sales)			0.00		0.00			0.00		0.00
			(0.00)		(0.00)			(0.00)		(0.00)
ln(Input-MA)				–0.00	–0.00				–0.00	–0.00
				(0.00)	(0.00)				(0.00)	(0.00)
Region-Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Conglomerate FE		✓			✓		✓			✓
Adj. R^2	0.14	0.20	0.14	0.14	0.20	0.16	0.27	0.16	0.16	0.27
# cluster (region)	60	60	60	60	60	60	60	60	60	60
# cluster (conglomerate)	1423	1422	1423	1423	1422	1423	1422	1423	1423	1422
N	2706	2705	2706	2706	2705	2706	2705	2706	2706	2705

Notes. This table reports the OLS estimates of Equation (1.4). When we construct the spillover measure defined in Equation (1.2), we lag firms' adoption status by five years. In columns (1)-(5), the dependent variables are a dummy variable of whether a firm makes a new technology adoption contracts made in a given year. In columns (6)-(11), the dependent variables are the inverse hyperbolic sine transformation of the number of new technology adoption contracts made in a given year. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (1.5) and (1.6). In all specifications, we control for region-sector fixed effects and the initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4.7 Matching Algorithm

This section describes the matching algorithm used for matching a loser to a winner for Section 1.4.1. Let $\mathbf{X} \in \mathcal{R}_k$ denotes the k-dimensional observable variables. The matching proceeds in two steps.

1. Pick two subsets of variables $\mathbf{X}^e \in \mathbf{X}$ that are exactly matched and $\mathbf{X}^d \in \mathbf{X}$ that are distance matched.

2. For each loser f, pick an adopter g such that

   - both firms have the same values of the variables of $\mathbf{X}^e$ with a loser f, then
   - minimize the Mahalanobis distance with loser f in terms of $\mathbf{X}^d$:

   $$\text{adopter}_g \in \arg\min_{g' \in \mathcal{F}} \{((\mathbf{X}_f^d - \mathbf{X}_g^d)'\mathbf{S}^{-1}(\mathbf{X}_f^d - \mathbf{X}_g^d)\},$$

   where $\mathcal{F}$ is a set of firms, $\mathbf{S}$ is the sample covariance of $\mathbf{X}^d$, and $\mathbf{X}_f^d$ and $\mathbf{X}_g^d$ represent the variables of firms f and g that are distance matched, respectively.

While we implement this matching algorithm, we pick regions and sectors as $\mathbf{X}^e$, and log assets as $\mathbf{X}^d$. Because we are exactly matching on regions and sectors, our matching procedure absorbs out any region-sector level common shocks, costs of production, and market size. By distance matching on log assets, we can compare winners and losers with similar size.

A.4.8 Production Function Estimation

In this section, we discuss the procedure we use to estimate revenue TFP measures. We obtain the revenue TFP measures as the residuals after estimating production using the methodologies in Wooldridge (2009), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and OLS. We estimate the following the Cobb-Douglas value added production function as follows:

$$\log VA_{it} = \alpha_L \log L_{it} + \alpha_K \log K_{it} + u_{it},$$

where VA_{it} is value added; L_{it} is employment; K_{it} are fixed assets; and α_L and α_K are Cobb-Douglas labor and capital shares.

When we use the methodologies developed by Wooldridge (2009), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), we use material inputs as a proxy variable. However, information on material inputs is not available for our main firm-balance sheet data digitized from the Annual Reports of Korean Companies. Therefore, we estimate the production function separately for each sector using alternative firm-level data. We used KIS-VALUE from 1980 to 1990. The Act on External Audits of Joint Stock Corporations, which was introduced in 1981, required South Korean firms whose assets were above 3 billion Korean Won to report their balance sheet data. That data is the source for KIS-VALUE. The coverage of our dataset is larger than KIS-VALUE. Also, because we observe sales but not value added, we calculate value added as sales times the value added shares from the input-output tables of corresponding years. Using these estimated coefficients from KIS-VALUE, we obtain revenue TFP for the sample period from 1970 to 1982.

A.5 Appendix: Quantification

A.5.1 Additional Figures

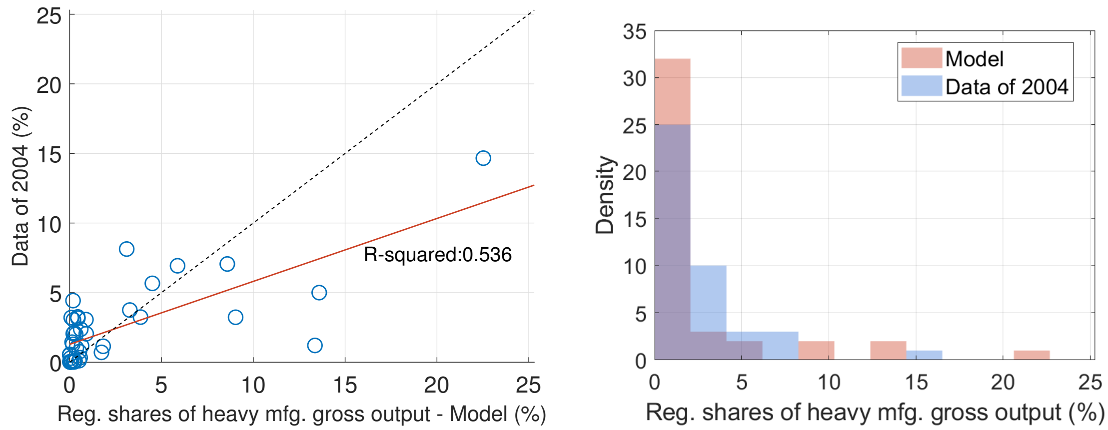
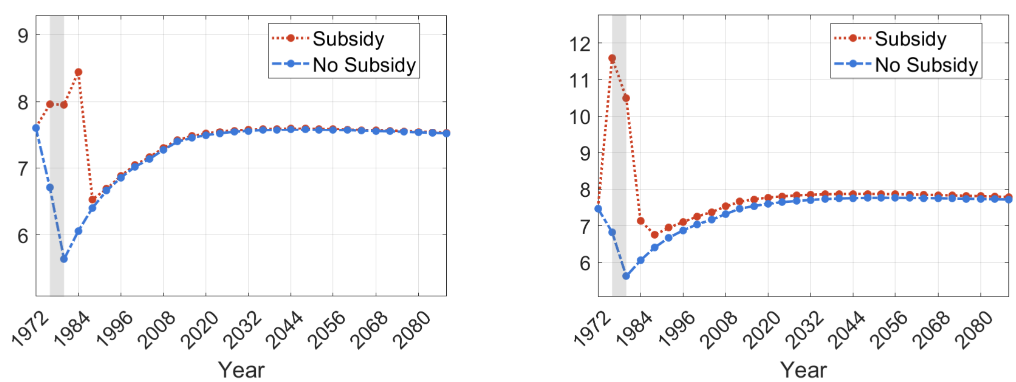


Figure A.9: Non-targeted Moments: Spatial Distribution of the Heavy Manufacturing's Gross Output

Notes. This figure compares regional shares of the heavy manufacturing sector obtained from the data in 2004 and those calculated from the model of the corresponding model period. To calculate the regional shares of the data, we use the Mining and Manufacturing Survey that covers the universe of establishments with more than 5 employees. X and y-axes of Panel A are regional shares computed from the model and the data counterpart, respectively. The red solid line of Panel A is the linear fit. Panel B plots the histogram of the regional shares of the data and the model.

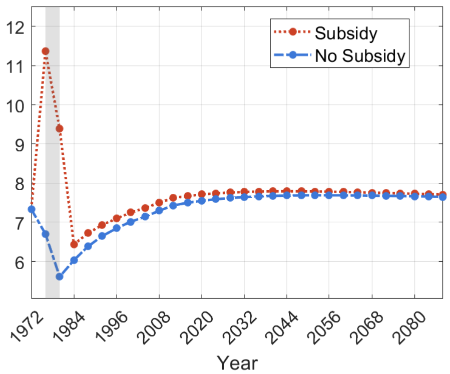


Heavy mfg. share of GDP (%)

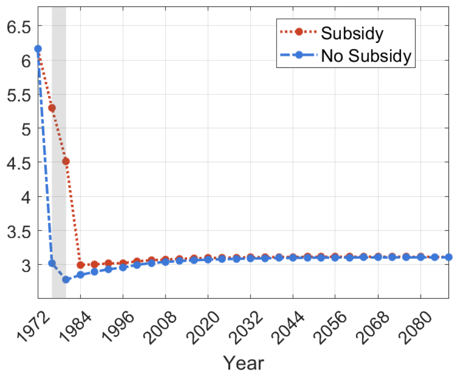
A. Low η B. Low δ

Figure A.10: Comparative Statistics of δ and η

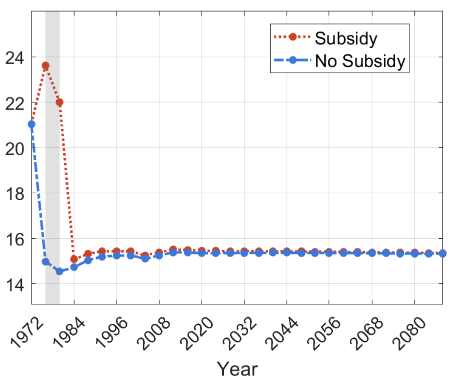
Notes. This figure plots the comparative statistics of δ and η. In Panel A, we set η to be 1.05. In Panel B, we set δ to be 1. The red dotted line and the blue dashed lines plot the outcomes of the baseline and counterfactual economies.



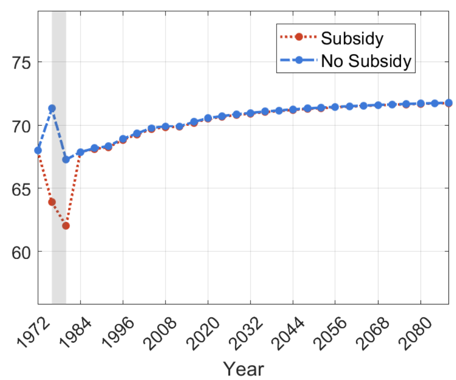
A. Heavy mfg. share of GDP (%)



B.Heavy mfg. share of employment (%)



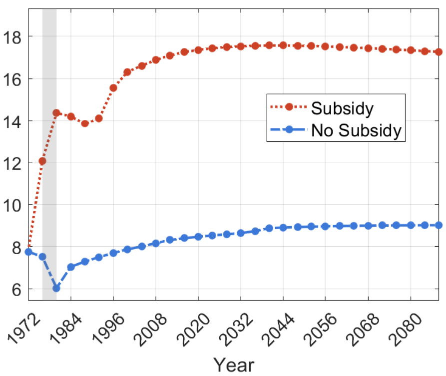
C. Heavy mfg. share of export (%)



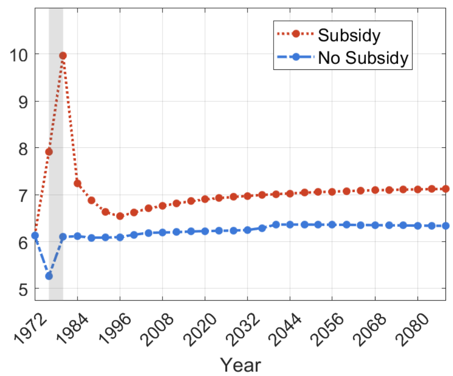
D. Light mfg. share of (%)

Figure A.11: The Effects of the Temporary Subsidies When there is No Roundabout Production Structure

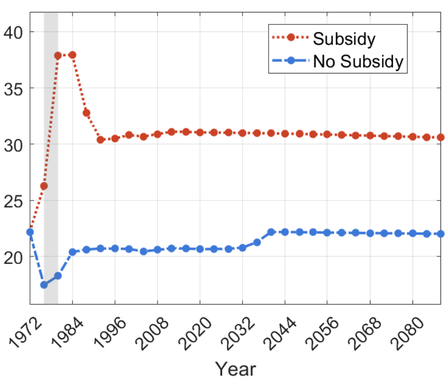
Notes. This figure plots counterfactual results without a roundabout production structure. Panels A, B, C, and D report the results for the heavy manufacturing sector employment, GDP, and export shares, and the light manufacturing sector export shares, respectively. The red dotted line plots the outcomes of the baseline economy and the blue dotted line plots the outcomes of the counterfactual economy.



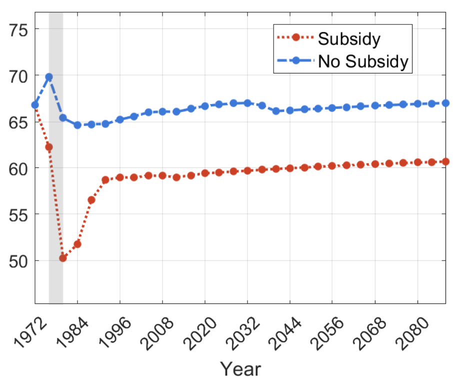
A. Heavy mfg. share of GDP (%)



B.Heavy mfg. share of employment (%)



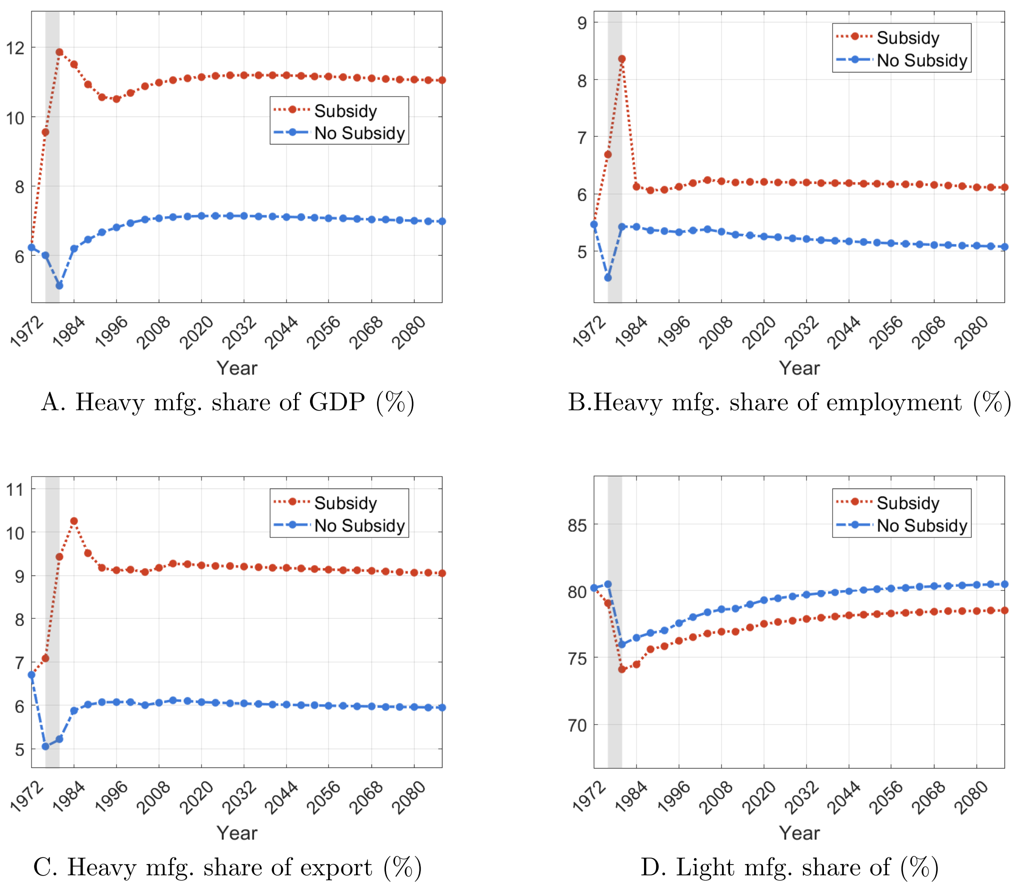
C. Heavy mfg. share of export (%)



D. Light mfg. share of (%)

Figure A.12: The Effects of the Temporary Subsidies with Higher Migration Costs

Notes. This figure plots counterfactual results with a 10% higher level of migration costs than the calibrated value in the baseline economy. The red line plots the outcome of the baseline economy and the blue line plots the outcome of the counterfactual economy.



A. Heavy mfg. share of GDP (%)

B.Heavy mfg. share of employment (%)

C. Heavy mfg. share of export (%)

D. Light mfg. share of (%)

Figure A.13: The Effects of the Temporary Subsidies When Foreign Market Size is Smaller

Notes. This figure plots counterfactual results with a lower level of foreign market size than the calibrated values in the baseline economy. The red line plots the outcome of the baseline economy and the blue line plots the outcome of the counterfactual economy.

A.5.2 Calibration Procedure

Data Inputs. The quantitative exercises requires the following data inputs:

- Aggregate data

  1. Initial conditions:

     - Initial shares of adopters in the previous period:

       $\{\lambda^T_{njt_0}\}_{n\in\mathcal{N},j\in\mathcal{J}^T,t_0=1968}$

     - Initial population distribution: $\{L^{Data}_{nt_0}\}_{n\in\mathcal{N},t_0=1968}$

  2. Sectoral gross output of each region:

     $\{GO^{Data}_{njt}\}_{n\in\mathcal{N},j\in\mathcal{J},t\in\{1972,1976,1980\}}$

  3. Regional population:

     $\{L^{Data}_{nt}\}_{n\in\mathcal{N},t\in\{1972,1976,1980\}}$

  4. Sectoral export shares at the national level:

     $\{EX^{Data}_{jt}/GO^{Data}_{jt}\}_{j\in\mathcal{J},t\in\{1972,1976,1980\}}$ where EX^{Data}_{jt} and GO^{Data}_{jt} are sector j's exports and gross output at the national level

  5. Sectoral import shares at the national level:

     $\{IM^{Data}_{jt}/E^{Data}_{jt}\}_{j\in\mathcal{J},t\in\{1972,1976,1980\}}$ where IM^{Data}_{jt} and E^{Data}_{jt} are imports and total expenditure on sector j goods at the national level

  6. Import and export tariffs:

     $\{t^{im}_{jt}\}_{j\in\mathcal{J},t\in\{1972,1976,1980\}}$ and $\{t^{ex}_{jt}\}_{j\in\mathcal{J},t\in\{1972,1976,1980\}}$

- Micro moments

  1. Identifying moment $\hat{\beta}^{policy}$ (Equation (1.31))
  2. Median of light and heavy mfg. shares of exports in 1972 across regions
  3. Median of heavy mfg. shares of adopters in 1972 and 1982 across regions
  4. Percent of zero adoption regions in 1972 and 1982

Algorithm. Taking the values of $\mathbf{\Theta}^E$ and data inputs as given, we obtain the values of $\mathbf{\Theta}^M$, $\{\bar{s}\}_{t\in\{1976,1980\}}$, and $\mathbf{\Psi}_t$ using the following calibration algorithm:

1. Guess parameters.
2. Guess fundamentals $\{c_{fj}, D_{fj}\}_{j\in\mathcal{J}}$, $\{V_{nt}\}_{n\in\mathcal{N}}$, and $\{\phi_{nj}^{min}\}_{n\in\mathcal{N},j\in\mathcal{J}}$
3. Given parameters $\{\mathbf{\Theta}^M, \bar{s}_t\}$, we solve the model and update the fundamentals $\mathbf{\Psi}_t$ for each period. Then, we fit region- and sector level aggregate outcomes to the data counterparts. This step corresponds to the constraints of Equation (1.29). For $t = 1$, we take the initial conditions from the data inputs as given. For $t = 2, 3$, we compute the initial conditions from the model outcomes in the previous period.
   (a) Update new $\{D_{jt}^{f'}\}$ using the following equation:
$$\underbrace{\frac{\mathrm{EX}_{jt}^{Data}}{\mathrm{GO}_{jt}^{Data}}}_{\text{Data}} = \underbrace{\frac{\sum_{n\in\mathcal{N}}\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}t_{jt}^{ex}\tau_{nj}^{x}}{\bar{\phi}_{njt}^{avg,x}}\right)^{1-\sigma}D_{jt}^{f'}}{\sum_{n\in\mathcal{N}}\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}}{\bar{\phi}_{njt}^{avg}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}}\tau_{nmj}P_{mjt}^{\sigma-1}E_{mjt}\right)+\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}t_{jt}^{ex}\tau_{nj}^{x}}{\bar{\phi}_{njt}^{avg,x}}\right)^{1-\sigma}D_{jt}^{f'}}}_{\text{Model}}$$
   (b) Update new $\{c_{fj}'\}$ using the following formula:
$$\underbrace{\frac{\mathrm{IM}_{jt}^{Data}}{\mathrm{E}_{jt}^{Data}}}_{\text{Data}} = \underbrace{\frac{\sum_{n\in\mathcal{N}}\left(\tau_{nj}^{x}t_{jt}^{im}c_{jt}^{f'}/P_{njt}\right)^{1-\sigma}E_{njt}}{\sum_{n\in\mathcal{N}}E_{njt}}}_{\text{Model}}$$
   (c) Update new $\{V_{nt}'\}$ until the population outcome of the model fits the actual distribution of population:
$$\underbrace{L_{nt}^{Data}}_{\text{Data}} = \underbrace{\sum_{m\in\mathcal{N}}\frac{\left(V_{nt}'\frac{(1-\tau_t^w+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\right)^{\nu}}{\sum_{n'=1}^{N}\left(V_{n't}'\frac{(1-\tau_t^w+\bar{\pi}_t^h)w_{n't}}{P_{n't}}d_{mn'}\right)^{\nu}}L_{mt-1}}_{\text{Model}}.$$
   Only relative levels of $\{V_{nt}'\}$ are identified from the above equation, so we normalize the value of the amenity of the first region to be 1 for each period: $V_{1t}' = 1, \forall t$.

(d) Update new $\{\phi_{nj}^{min'}\}$ until shares of regional gross output are exactly fitted to the data counterparts:

$$\underbrace{\frac{GO_{njt}^{Data}}{\sum_{m\in\mathcal{N}}\sum_{k\in\mathcal{J}} GO_{mkt}^{Data}}}_{\text{Data}} =$$

$$\underbrace{\frac{\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}}{\bar{\phi}_{njt}^{avg}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}}\tau_{nmj}P_{mjt}^{\sigma-1}E_{mjt}\right)+\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}t_{jt}^{ex}\tau_{nj}^{x}}{\bar{\phi}_{njt}^{avg,x}}\right)^{1-\sigma}D_{jt}^{f'}}{\sum_{n'\in\mathcal{N}}\sum_{k'\in\mathcal{J}}\left(\frac{\sigma}{\sigma-1}\frac{c_{n'k't}}{\bar{\phi}_{n'k't}^{avg}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}}\tau_{n'mk'}P_{mk't}^{\sigma-1}E_{mk't}\right)+\left(\frac{\sigma}{\sigma-1}\frac{c_{n'k't}t_{k't}^{ex}\tau_{n'k'}^{x}}{\bar{\phi}_{n'k't}^{avg,x}}\right)^{1-\sigma}D_{k't}^{f'}}}_{\text{Model}},$$

The above equations only identify the relative levels of $\{\phi_{njt}^{min'}\}$, so we normalize the Pareto lower bound parameter of the first region and sector pair to 1 for each period: $\phi_{11t}^{min'} = 1, \forall t$.

4. After updating the geographic fundamentals, given values of parameters and subsidies, we evaluate the following objective function:

$$(m(\{\mathbf{\Theta}^M, \mathbf{s}_t\}) - \bar{m}^{Data})'\mathbf{W}(m(\{\mathbf{\Theta}^M, \mathbf{s}_t\}) - \bar{m}^{Data}),$$

where $m(\Theta)$ is the moments from the model, $\bar{m}^{Data}$ is the data counterparts, and $\mathbf{W}$ is the weighting matrix. We use the identity matrix for the weighting matrix.

5. For each value of $\{\mathbf{\Theta}^M, \mathbf{s}_t\}$, we iterate steps 2, 3, and 4 and find the values of $\{\hat{\mathbf{\Theta}}^M, \hat{\mathbf{s}}_t\}$ that minimize the objective function in the step 4.

A.5.3 Construction of Data Inputs

In this section, we describe how we constructed data inputs for the calibration procedure. We aggregate 10 manufacturing sectors into light and heavy manufacturing sectors.

Aggregate Data

Initial Shares of Adopters in 1968. While our firm balance sheet data covers from 1970 to 1982, technology adoption contracts cover from 1966 to 1985. We do not directly observe firm balance sheet data in 1968. Therefore, we use the information on the start year of firms to construct a set of firms that were operating in 1968. Then, we merge this set of firms with our data about their adoption activities and construct shares of adopters in the heavy manufacturing sector for each region.[15]

Regional Population Distributions in 1968, 1972, 1976, and 1980. The regional population data comes from the Population and Housing Census, the 2% random sample of the total population. The survey was conducted in 1966, 1970, 1975, and 1980. For the years not covered by this Census survey, we impute population using the geometric average of the two observed samples. For example, the population share of region n in 1973 is imputed as $\text{Pop. share}_{n,1973} = (\text{Pop. share}_{n,1970})^{\frac{3}{5}} \times (\text{Pop. share}_{n,1975})^{\frac{2}{5}}$. From these imputed values, we obtain regional population in 1968, 1972, 1976, and 1980. The regional population distribution in 1968 is the initial condition that is taken as given in the model when solving for $t = 1$, whereas the regional population distributions in 1972, 1976, and 1980 are fitted by the regional population distributions of the model at $t = 1, 2, 3$, which are the endogenous outcomes of the model.

Regional and Sectoral Level Gross Output in 1972, 1976, and 1980. We compute gross output at the regional and sectoral level by harmonizing firm-level data and data from input-output tables following di Giovanni et al. (2020). Using firm-level

[15] Given the facts that we cannot observe entry and exit of firms in 1968 and 1969 and we construct the shares based on the firms that operated in 1970 and these firms' start year.

data, we calculate a share of firm sales in region n and sector j and then multiply this share by the gross output of sector j at the national level. Specifically, we calculate

$$GO_{njt}^{Data} = \left(\frac{\sum\limits_{i \in nj} Sale_{it}}{\sum\limits_{m \in \mathcal{N}} \sum\limits_{k \in \mathcal{J}} \sum\limits_{i \in mk} Sale_{it}} \right) \times GO_{jt}^{IO},$$

where GO_{jt}^{IO} is sector j's gross output from the input-output tables. By doing so, we preserve the spatial distribution of firm sales but ensures that the total sum of sales across firms is consistent with the national input-output tables for each year.

Aggregate Export and Import Shares in 1972, 1976, and 1980. Both aggregate export and import shares are obtained from the national input-output tables. We calculate aggregate export share as $EX_{jt}^{Data}/GO_{jt}^{Data}$, where EX_{jt}^{Data} is sector j's exports of the input-output tables. In the model, we treat the service sector as a non-tradable sector, so we assume that exports and imports of the service sector are zero. We calculate aggregate sectoral import share is calculated as $IM_{jt}^{Data}/E_{jt}^{Data}$, where IM_{jt}^{Data} represent imports of sector j and E_{jt}^{Data} represent expenditures of sector j. We calculate E_{jt}^{Data} as follows:

$$E_{jt}^{Data} = \alpha_j \sum_{k \in \mathcal{J}} \left(\gamma_k^L \frac{\sigma - 1}{\sigma} GO_{kt}^{IO} \right) + \sum_{k \in \mathcal{J}} \gamma_k^j \frac{\sigma - 1}{\sigma} GO_{kt}^{IO},$$

where GO_{jt}^{IO} is sector j's gross output from the input-output table in year t.

Export and Import Tariffs Data in 1972, 1976, and 1980. We use data on export and import tariffs data are not used for the reduced-form empirical analysis but only for the quantitative exercises and not for the reduced-form empirical analysis. We obtain the data on export tariffs from Magee (1986).[16] The original dataset's industry code is in four-digit 1972 SIC codes. We first convert those codes into four-digit 1987 SIC codes and then into ISIC Revision 3 codes.[17]

[16] We download the United States export tariff data from `https://cid.econ.ucdavis.edu/ust.html`.

[17] The concordance between 1972 SIC and 1987 SIC is obtained from `https://www.nber.com`.

We digitize import tariff data from Luedde-Neurath (1986) for 1974, 1976, 1978, 1980, and 1982, which are in the Customs Cooperation Council Nomenclature (CCCN). We convert CCCN to ISIC Revision 3 and then average the results across four-digit ISIC codes. For missing years, we impute values using the geometric average. We assume that the tariff level in 1972 was the same as that in 1974.

We aggregate trade tariffs up to four sectors for each year by taking the average across sectors. We do not use the weighted average, where the weight is given by import values. The weighted average gives zero weight to sectors with zero import values, which can underestimate the magnitude of the tariffs.

Micro moments

We compute shares of adopters for each year using our dataset. After computing these shares across regions and years, we compute the median for 1972 and 1980. Using this information, we compute shares of regions with zero values. We also obtain shares of exporters. However, because of many missing data points on exports, we take the three-year moving averages of shares of exports for each region and sector. We count firms with missing information on exports as non-exporters. Section A.5.4 describes how we calculate the identifying moment in more detail.

A.5.4 The Identifying Moment for Subsidy

Calibration Procedure. Using data on regional shares of adopters within the heavy manufacturing sector across regions in 1972 and 1980, we run the following regression model via PPML:

$$\ln \lambda^T_{n,heavy,t} = \alpha + \beta^{policy} \times D^{policy}_t \beta_1 \lambda^T_{n,heavy,t-1} + \epsilon_{n,heavy,t},$$

where D^{policy}_t is a dummy variable that equals 1 in 1980 and $\lambda^T_{n,heavy,t}$ are heavy manufacturing sector's shares of adopters in region n in period t. One period of the model corresponds to four years in the data, so $\lambda^T_{n,heavy,t-1}$ is lagged by four years. We cluster standard errors at the regional level. The estimated coefficients are reported in Table A.18.

Table A.18: Identifying Moment for Subsidy Rate

Dep. Var. $\lambda^T_{n,heavy,t}$	(1)
D^{policy}_t	0.65**
	(0.25)
$\lambda^T_{n,heavy,t-1}$	5.62***
	(0.80)
# of clusters (region)	42
N	84

Notes. This table reports the OLS estimates. Standard errors are clustered at region level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We run the same regression model using the model-generated data. Following Silva and Tenreyro (2006), we calculate the estimate of β^{policy} by solving the first-order condition of log likelihood of PPML:

$$\sum_{n \in \mathcal{N}} \mathbf{X}_{nt}(\lambda^T_{n,heavy,t} - exp(\mathbf{X}'_{nt}\boldsymbol{\beta})),$$

where $\boldsymbol{\beta} = [\alpha, \beta^{Policy}, \beta_1]'$ and $\mathbf{X}_{nt} = [1, D^{policy}_t, \lambda^T_{n,heavy,t-1}]$.

Connection with Proposition I.4. Note that the assumptions of Proposition I.4 are not satisfied in the data or the model and we run the regression only for the heavy manufacturing sector. However, we can show that $\hat{\beta}^{policy}$ is still informative for $\bar{s}$.

Under the unbounded Pareto distributional assumption, we can derive the following relationship from the model for the heavy manufacturing sector without any additional assumptions:

$$\ln \lambda^T_{n,heavy,t} - \theta\delta\lambda^T_{n,heavy,t-1} =$$
$$\underbrace{\frac{\theta}{\sigma-1}\ln\left(\left(\frac{\eta}{1-s_{n,heavy,t}}\right)^{\sigma-1}-1\right)\underbrace{-\theta\ln\left(\frac{\mu c_{n,heavy,t}(\sigma c_{n,heavy,t}F^T_{heavy})^{\frac{1}{\sigma-1}}}{(\sum_{m\in\mathcal{N}} P^{\sigma-1}_{heavy,t}E_{m,heavy,t}+D^f_{heavy,t})^{\frac{1}{\sigma-1}}}\right)}_{=\mathbf{GE}_{n,t}(\mathbf{\Psi}_t,\mathbf{s}_t)}}_{=D^{policy}_t}$$
$$+\underbrace{\theta\ln\phi^{min}_{n,heavy,t}}_{=\epsilon_{n,heavy,t}}.$$

Because the heavy manufacturing sector is the only sector that adopted technology and the only sector the government targeted, we can not identify D^{policy}_t separately from additional time fixed effects.

D^{policy}_t captures both the subsidies in the second term of the right hand side and the general equilibrium effects in the third term of the right hand side. $\mathbf{GE}_{n,t}(\mathbf{\Psi}_t,\mathbf{s}_t)$ depend all other regions' geographic fundamentals $\mathbf{\Psi}_t$ and subsidies $\mathbf{s}_t$. $\mathbf{GE}_{n,t}(\mathbf{\Psi}_t,\mathbf{s}_t)$ is a function of own exogenous natural advantage in the error term and therefore is correlated with the error term. This leads to the endogeneity problem of the regression model above. In Proposition I.4, we could absorb out these general equilibrium effects using region fixed effects by imposing the additional assumptions. However, that is not the case in the regression model above.

However, although $\hat{\beta}^{policy}$ is biased, it is still informative for $\bar{s}$. For given values of $\bar{s}$ and other structural parameters, we back out geographic fundamentals by exactly fitting region- and sector-level data. From these obtained geographic fundamentals, we can compute the error term and the general equilibrium effects. Therefore, our indirect inference for fitting $\hat{\beta}^{policy}$ can be thought of fitting the joint effects of both the subsidies in the second term and $\mathbf{GE}_{n,t}(\mathbf{\Psi}_t, \mathbf{s}_t)$.

A.5.5 Gravity Equation of Migration Flows

The data on migration shares comes from the 1995 Population and Housing Census, which is the closest to the sample period of our dataset among the accessible population census data. Because of data availability, regions are aggregated into 35 groups. μ_{nm1990}^{1995} is obtained as the total number of migrants moving from region n to region m from 1990 to 1995 divided by the total population of region n in 1990. When we compute the total population and the number of migrants, we restrict our sample age to 20 to 55. We also exclude outward migration flows from Jeju Island and inward migration flows to Jeju Island.

We parametrize migration costs as a function of distance between two regions $dist_{mn}$ and an error term ϵ_{mnt}^{d} that is orthogonal to the distance between two regions: $d_{mn} = (dist_{mn})^{-\zeta}\epsilon_{mnt}^{d}$. Taking the log of Equation (1.16), we derive the following regression model:

$$\ln \mu_{mn1990}^{1995} = -\nu\zeta \log dist_{mn} + \underbrace{\ln\left(V_{n,1995}\frac{(1-\bar{\tau}_{1995}^{w}+\bar{\pi}_{1995}^{h})w_{nt}}{P_{n,1995}}\right)}_{=\delta_n}$$
$$+ \underbrace{\ln\left(\sum_{n'=1}^{N}\left(V_{n',1995}\frac{(1-\tau_{1995}^{w}+\bar{\pi}_{1995}^{h})w_{n',1995}}{P_{n'1995}}d_{mn'}\right)^{\nu}\right)}_{\delta_m} + \epsilon_{mnt}^{d},$$

which gives Equation (1.28). We estimate the above equation using OLS and PPML. The results are reported in Table A.19. The estimated coefficient is around -1.30. The magnitude of the estimate implies that a 1 percent increase in distance decreases the share of outward migration by 1.3%.

Table A.19: Gravity Equation of Migration Shares

Dep. Var.	Migration Shares from 1990 to 1995	
	OLS	PPML
	(1)	(2)
$LogDist_{mn}$	–1.30***	–1.39***
	(0.06)	(0.03)
Adj. R^2	0.88	.
# clusters (origin)	35	35
# clusters (destination)	35	35
N	1210	1225

Notes. This table reports the gravity estimates of Equation (1.28). The dependent variable is the log of the share of migration from region m to region n from 1990 to 1995. In column (1), we estimate the model using OLS. In column (2), we estimate the model using the Poisson pseudo-maximum likelihood estimation (Silva and Tenreyro, 2006). Clustered errors are two-way clustered at the origin and destination levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX B

Appendices to Chapter 2

B.1 Data

B.1.1 Data Construction

Firm Balance Sheet. For the sample period between 1970 and 1982, firm balance sheet data are digitized from the historical Annual Report of Korean Companies published by the Korea Productivity Center. The annual reports have information on assets, capital, employment, export, fixed assets, and sales. For the sample between 1980 and 2011, firm balance sheet data comes from KIS-VALUE and FnGuide. The two separate data sets are then merged based on firm names.

The coverage of the Annual Report of Korean Companies is broader than KIS-VALUE or FnGuide. KIS-VALUE and FnGuide cover firms with assets above 3 billion Korean Won. In contrast, the Annual Report of Korean Companies (1973-1983) covers firms with capital larger than 50 million Korean Won, including more small and medium-sized firms. Therefore, in the main data set, we restrict our sample to the firms appearing in both KIS-VALUE or FnGuide and Annual Report of Korean Companies.

Foreign Credit. The data of foreign credit allocated by the government was hand-collected and digitized from the national historical archives. Key variables are the total amount borrowed, interest rate, and repayment period for each financial contract. Foreign credit data are merged with firm-balance sheet data based on firm names.

Figure B.1, B.2, and B.3 displays the examples of the financial contract documents of Hyundai International Inc., which borrowed from seven foreign banks or companies.[1] Hyundai International INC. borrowed \$44M at interest rate 8.375%. Figure B.3 is the first page of the formal contract document between Hyundai International Inc. and the foreign banks. Importantly, it shows that the Korea Development Bank, the state-owned policy development bank that was in charge of financing industrial policies conducted by the government, guaranteed the repayment of this contract.

Table B.1 reports the descriptive statistics of the collected credits data. The table reports the mean, standard deviation, maximum, and minimum of credit amounts, repayment periods, and interest rates.

Table B.1: Descriptive Statistics of Foreign Credit Data

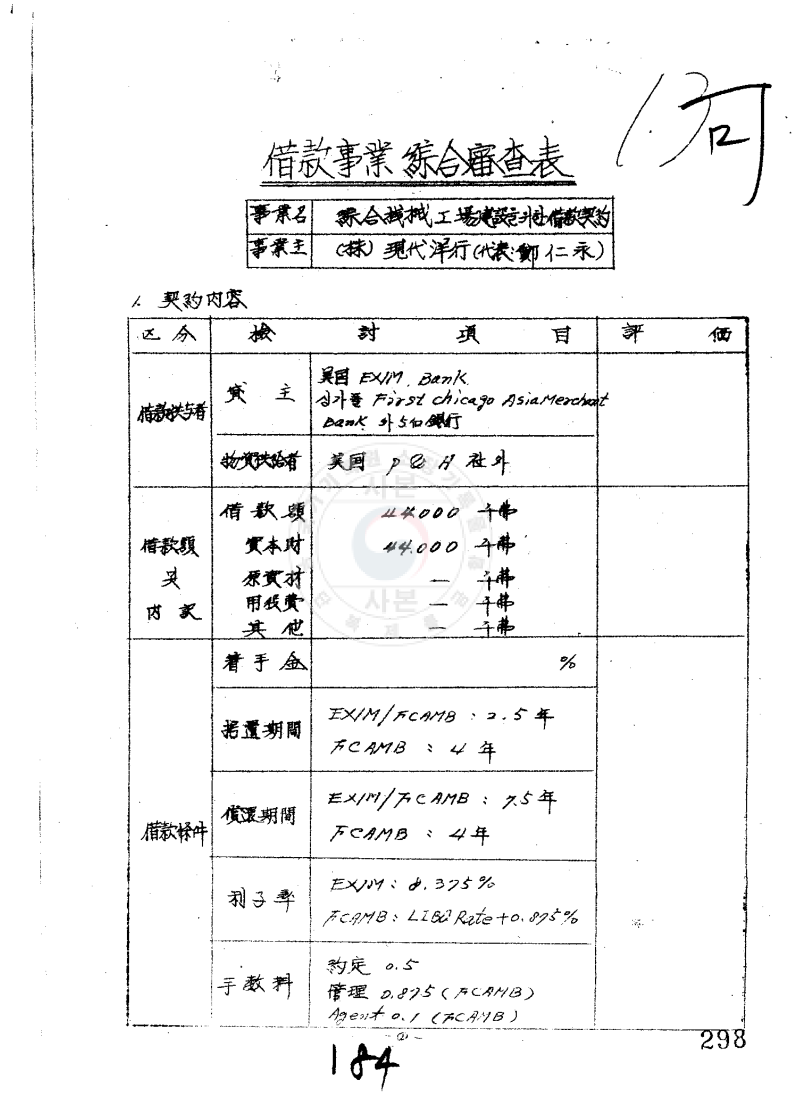
	(1) Loan Size (mln 2015 USD)	(2) Repayment Period (years)	(3) Interest Rate (%)
Mean	47.0	6.17	8.97
Std.	74.2	2.23	2.01
Max.	540.2	15	16.9
Min.	0.70	0.50	0
N	538	538	538

Notes. This table reports the descriptive statistics of approved financial contracts between domestic firms and foreign entities from 1973 to 1979.

Input Output Table. Input-Output tables are obtained from the Bank of Korea. Based on the descriptions of the products, we convert the reported codes into ISIC

[1] These seven foreign banks or companies are First Chicago Hong Kong Ltd., Bank Bumiputra Malaysia Berhad, Credit Lyonnais Hong Kong (Finance) Ltd., Nippon Credit International (HK) Ltd., Toronto Dominion Investments (HK) Ltd., Export-Import Bank of the United States (EXIM), and First Chicago Asia Merchant Bank Ltd..

Figure B.1: An Example of a Financial Contract Digitized from the Historical Archive



借款事業 綜合審査表

事業名	綜合機械工場建設을 위한 借款契約
事業主	(株) 現代洋行 (代表: 鄭仁永)

1. 契約內容

区分	検討項目		評価
借款供与者	貸主	美国 EXIM. Bank 싱가폴 First chicago Asia Merchant Bank 外 5個銀行	
	物資供給者	美国 P & H 社 外	
借款額 및 內訳	借款額	44,000 千弗	
	資本財	44,000 千弗	
	原資材	— 千弗	
	用役費	— 千弗	
	其他	— 千弗	
借款條件	着手金	%	
	据置期間	EXIM/FCAMB : 2.5 年 FCAMB : 4 年	
	償還期間	EXIM/FCAMB : 7.5 年 FCAMB : 4 年	
	利子率	EXIM : 8.375 % FCAMB : LIBO Rate + 0.875 %	
	手数料	約定 0.5 管理 0.875 (FCAMB) Agent 0.1 (FCAMB)	

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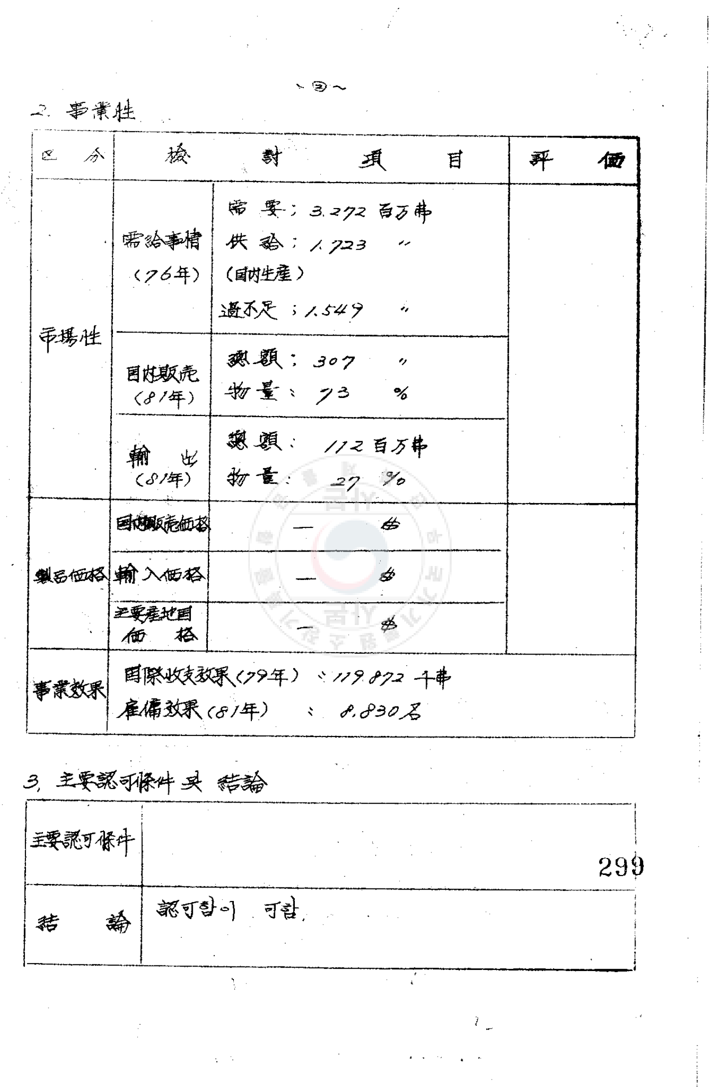
Rev.3. From the Input-Output table, we obtain value-added shares and intermediate input shares.

Trade and Import Tariffs. Trade data between 1972 and 2000 come from Feenstra et al. (2005), which come in the 4-digit Standard International Trade Classification (SITC) classification. We convert SITC into ISIC Rev 3. Import tariffs data is digi-

Figure B.2: An Example of a Financial Contract Digitized from the Historical Archive-cont'd



~②~

2. 事業性

区分	検討項目		評価
市場性	需給事情 (76年)	需要 ; 3.272 百万弗 供給 ; 1.723 〃 (国内生産) 過不足 ; 1.549 〃	
	国内販売 (81年)	總額 ; 307 〃 物量 ; 73 %	
	輸出 (81年)	總額 ; 112 百万弗 物量 ; 27 %	
製品価格	国内販売価格	— $	
	輸入価格	— $	
	主要産地国価格	— $	
事業效果	国際収支效果 (79年) : 119.872 千弗 雇傭效果 (81年) : 8.830 名		

3. 主要認可條件 및 結論

主要認可條件	
結論	認可함이 可함.

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tized from Luedde-Neurath (1986), which come in the Customs Co-operation Council Nomenclature (CCCN). We convert CCCN into 4-digit ISIC Rev 3. The average import tariffs are obtained as the averaged import tariffs across 4-digit ISIC sectors, weighted by import values.

Figure B.3: An Example of a Financial Contract Digitized from the Historical Archive-cont'd

HYUNDAI INTERNATIONAL, INC.
(as Borrower)

THE KOREA DEVELOPMENT BANK
(as Guarantor)

FIRST CHICAGO HONG KONG LIMITED

BANK BUMIPUTRA MALAYSIA BERHAD

CREDIT LYONNAIS HONG KONG (FINANCE) LIMITED

NIPPON CREDIT INTERNATIONAL (HK) LIMITED

TORONTO DOMINION INVESTMENTS (HK) LIMITED

EXPORT-IMPORT BANK OF THE UNITED STATES
(as Lenders)

FIRST CHICAGO ASIA MERCHANT BANK LTD.
(as Agent)

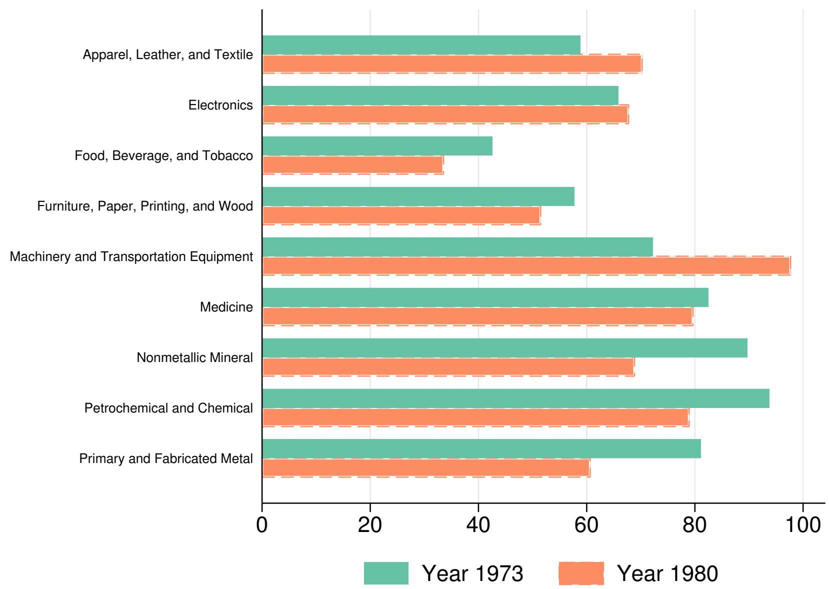
Credit Agreement

Korea | Eximbank Credit No. 6500

~~242~~ 390

B.1.2 Coverage of the Data Set

Figure B.4: Coverage of the Data Set (%)



Notes. This figure depicts the fraction of total sales in each sector that is covered by the firms in the dataset. Total sales in each sector come from the Input-Output tables.

B.1.3 List of Chaebol Groups

English and Corresponding Korean Names

- Geumho, Kia, Daerim, Daewoo, Taihan Electric Wire, Daehan Shipbuilding, Dongbu, Dong Ah, Doosan, Lucky, Lotte, Miwon, Sammi, Samsung, Samhwan, Sunkyung, Shindongah, Ssangyong, Jinyang, Kolon, Taekwang, Hanwha, Hanbo, Hanyang, Hanil Synthetic Fiber, Hanjin, Hyundai, Hyosung

B.1.4 Targeted Regions and Sectors

Table B.2: Targeted Regions

Region name	Specialized Sectors	Start Year of Industrial Complex
Busan	Rubber, Shipbuilding	No industrial complex
Changwon, Jinhae	Machinery	1975
Guje (Jukdo, Okpo)	Shipbuilding	1974
Gumi	Electronics	1973
Masan	Synthetic fibre	1970
Pohang	Metals, Steel	1967
Ulsan	Chemicals, Motor Vehicles, Petrochemicals, and Shipbuilding	1962
Yeosu, Yeocheon	Chemicals, Petrochemicals	1967

Table B.3: Sector Classification

HCI	Aggregated Industry	Industry
HCI	Chemicals, Petrochemicals, and Rubber and Plastic Products	Coke oven products (231) Refined petroleum products (232) Basic chemicals (241) Other chemical products (242) Man-made fibres (243) except for pharmaceuticals and medicine chemicals (2423) Rubber products (251) Plastic products (252)
	Electrical Equipment	Office, accounting and computing machinery (30) Electrical machinery and apparatus n.e.c. (31) Ratio, television and communication equipment and apparatus (32) Medical, precision, and optical instruments, watches and clocks (33)
	Basic and Fabricated Metals	Basic metals (27) Fabricated metals (28)
	Machinery and Transport Equipment	Machinery and equipment n.e.c. (29) Motor vehicles, trailers and semi trailers (34) Building and repairing of ships and boats (351) Railway and tramway locomotives and rolling stock (352) Aircraft and spacecraft (353) Transport equipment n.e.c. (359)
Non-HCI	Food, Beverages, and Tobacco	Food products and beverages (15) Tobacco products (16)
	Textiles, Apparel, Leather	Textiles (17) Apparel (18) Leather, luggage, handbags, saddlery, harness, and footwear (19) Manufacturing n.e.c. (369)
	Wood, Paper, Printing, and Furniture	Wood and of products, cork (20) Paper and paper products (21) Publishing and printing (22) Furniture (361)
	Pharmaceuticals and Medicine Chemicals	pharmaceuticals and medicine chemicals (2423)
	Other Non-Metallic Mineral Products	Glass and glass products (261) Non-metallic mineral products n.e.c. (269)

B.2 Estimation Results Appendix

Table B.4: First Stage. Short-Run Effects of Subsidies on Firms' Sales Growth

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:				$asinh(Credit)$		
IV	5.58***	5.43***	5.73***	5.58***	5.63***	5.67***
	(0.89)	(0.90)	(0.88)	(0.91)	(0.89)	(0.86)
$\log(Sales_{t_0})$	1.18***	1.00***	1.18***	1.18***	1.18***	1.03***
	(0.19)	(0.21)	(0.19)	(0.19)	(0.19)	(0.21)
$Chaebol$		3.58*				3.54*
		(1.96)				(1.89)
△Export Demands × $Port$			0.55			0.30
			(0.52)			(0.45)
△ log(Import Tariffs) × $Port$				–0.58		53.83
				(10.16)		(46.21)
△ log(Input Tariffs) × $Port$					–15.87	–120.91
					(20.53)	(88.19)
Adj. R^2	0.26	0.28	0.26	0.26	0.26	0.28
Num. Clusters	56	56	56	56	56	56
N	764	764	764	764	764	764

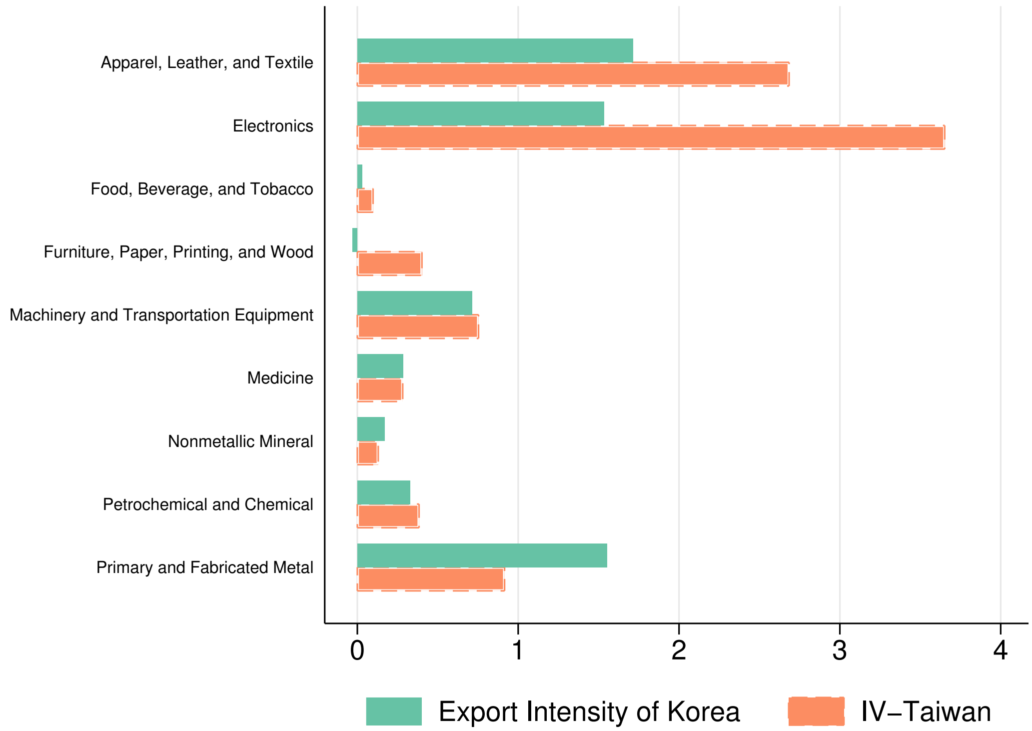
Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the first stage results of the short-run IV regression (2.1). The dependent variable is the inverse hyperbolic sine transformation of credits defined in (2.2). The IV is defined in (2.3). Chaebol is a dummy variable which equals one if a firm is affiliated with the top 30 Chaebol group. △*Export Demand* × *Port* is the interaction between the port dummies with the changes of the world demand shock defined in Equation (2.5). △*Import Tariff* × *Port* is the interaction between changes of import tariffs and the port dummy variable. △*Import Tariff* × *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in Equation (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects.

Table B.5: First Stage. Long-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$asinh(Credit)$					
	(1)	(2)	(3)	(4)	(5)	(6)
IV	3.17***	3.26***	3.53***	3.24***	3.35***	3.53***
	(0.84)	(0.86)	(0.78)	(0.82)	(0.81)	(0.78)
$\log(Sales_{t_0})$	1.93***	1.66***	1.94***	1.93***	1.93***	1.67***
	(0.28)	(0.26)	(0.29)	(0.29)	(0.29)	(0.25)
Chaebol		4.25*				4.21*
		(2.14)				(2.13)
$\triangle$Export Demands $\times$ $Port$			0.85*			0.27
			(0.50)			(0.56)
$\triangle$ log(Import Tariffs) $\times$ $Port$				–17.84*		4.19
				(7.89)		(55.56)
$\triangle$ log(Input Tariffs) $\times$ $Port$					–41.22***	–38.45
					(13.78)	(111.68)
Adj. R^2	0.32	0.35	0.32	0.32	0.32	0.35
Num. Clusters	54	54	54	54	54	54
N	738	738	738	738	738	738

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the first stage results of the short-run IV regression (2.1). The dependent variable is the inverse hyperbolic sine transformation of credits defined in (2.2). The IV is defined in (2.3). Chaebol is a dummy variable which equals one if a firm is affiliated with the top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in Equation (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in Equation (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects.

Figure B.5: Changes of Export Intensity of Korea and Export Intensity Measured by Exports of Taiwan



Notes. The figure plots South Korea's log-difference export intensity and the instrumental variable for South Korea's log-difference export intensity. The green bar plots South Korea's log-difference export intensity of sector j defined as the change in total exports divided by gross output in 1970. The orange bar plots the instrumental variable for the export intensity where South Korea's total exports are replaced with Taiwan's total exports of the same sector.

Table B.6: Robustness. Instrumenting Export Demand. Short-Run Effects of Subsidies on Firm Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1972-1981 and 1973-1982	
	(1)	(2)
$asinh(Credit)$	0.18***	0.17***
	(0.04)	(0.04)
$\triangle Export\ Demand^{KOR} \times Port$	–0.01	–0.01
	(0.15)	(0.15)
$\log(Sales_{it_0})$	–0.68***	–0.69***
	(0.05)	(0.04)
$Chaebol$		0.24
		(0.40)
Region FE	Y	Y
Sector FE	Y	Y
KP-F	21.20	20.12
SW-$F1$	42.39	40.44
SW-$F2$	146.50	166.19
Num. Clusters	56	56
N	764	764

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the IV estimates of (2.1). The dependent variable is sales growth between 1972 and 1981 or between 1973 and 1982. $asinh(Credit)$ and $\triangle Export\ Demand^{KOR} \times Port$ are instrumented by IVs in (2.3) and (2.5), where $\triangle Export\ Demand^{KOR} \times Port$ is the interaction between the port dummies with the changes of the world demand shock for Korea's exports. Chaebol is a dummy variable which equals one if a firm is affiliated with the top 30 Chaebol group. $\log(Sales_{it_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects. KP-F is the Kleinbergen-Paap F-statistics. SW-$F1$ and SW-$F2$ are Sanderson and Windmeijer (2016) F-statistics for $asinh(Credit)$ and $\triangle Export\ Demand^{KOR} \times Port$ respectively.

Table B.7: Robustness. Instrumenting Exports Demands. Long-Run Effects of Subsidies on Firm Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1981-2009 and 1982-2010	
	(1)	(2)
$asinh(Credit)$	0.50***	0.49***
	(0.13)	(0.13)
$\triangle Export\ Demand^{KOR} \times Port$	–0.40	–0.33
	(0.59)	(0.50)
$\log(sales_{it_0})$	–1.09***	–0.99***
	(0.31)	(0.27)
$Chaebol$		–1.37
		(1.48)
Region FE	Y	Y
Sector FE	Y	Y
KP-F	7.59	8.04
SW-$F1$	16.01	16.75
SW-$F2$	20.07	31.70
Num. Clusters	54	54
N	738	738

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the IV estimates of (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. $asinh(Credit)$ and $\triangle Export\ Demand^{KOR} \times Port$ are instrumented by IVs in (2.3) and (2.5), where $\triangle Export\ Demand^{KOR} \times Port$ is the interaction between the port dummies with the changes of the world demand shock for Korea's exports. Chaebol is a dummy variable which equals one if a firm is affiliated with the top 30 Chaebol group. $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F is the Kleinbergen-Paap F-statistics. SW-$F1$ and SW-$F2$ are Sanderson and Windmeijer (2016) F-statistics for $asinh(Credit)$ and $\triangle Export\ Demand^{KOR} \times Port$ respectively.

Table B.8: Robustness. No Initial Sales Control. Short-Run Effects of Subsidies on Firms' Sales Growth

Dep.	$\triangle \log Sales_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$asinh(Credit)$	0.02*	0.09*		0.09**	0.09**	0.09**	0.09**	0.10**
	(0.01)	(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
IV			0.59***					
			(0.22)					
$Chaebol$				–0.16				–0.21
				(0.33)				(0.35)
$\triangle Export\ Demand \times Port$					0.11			0.24*
					(0.08)			(0.13)
$\triangle \log(Import\ Tariff) \times Port$						1.99		10.25
						(2.23)		(6.39)
$\triangle \log(Input\ Tariff) \times Port$							1.62	–11.38
							(4.09)	(13.96)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		39.60		36.14	41.91	39.31	40.50	42.21
Adj. R^2	0.09		0.09					
Num. Clusters	56	56	56	56	56	56	56	56
N	764	764	764	764	764	764	764	764

Notes. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1972 and 1981 or between 1973 and 1982. The OLS estimates are reported in column 1. The IV estimates are reported in column 2, 4, 5, 6, and 7, where the IV is defined in Equation (2.3). In column 3, the reduced form estimates of the IV are reported. Chaebol is a dummy variable which equals one if a firm is affiliated with the top 30 Chaebol group. $\triangle Export\ Demand \times Port$ is the interaction between the port dummies with the changes of the world demand shock defined in Equation (2.5). $\triangle Import\ Tariff \times Port$ is the interaction between changes of import tariffs and the port dummy variable. $\triangle Import\ Tariff \times Port$ is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in Equation (2.7). Across all specifications, region and sector fixed effects are controlled. KP-F is the Kleinbergen-Paap F-statistics. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01.

Table B.9: Robustness. No Initial Sales Control. Long-Run Effects of Subsidies on Firms' Sales Growth

Dep.	$\triangle \log Sales_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$asinh(Credit)$	0.01	0.23***		0.25***	0.24***	0.23***	0.23***	0.25***
	(0.01)	(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
IV			1.39***					
			(0.17)					
$Chaebol$				–1.15				–1.19
				(1.01)				(1.01)
$\triangle Export\ Demand \times Port$					0.09			0.43**
					(0.17)			(0.19)
$\triangle \log(Import\ Tariff) \times Port$						1.09		–13.43
						(4.73)		(13.66)
$\triangle \log(Input\ Tariff) \times Port$							5.42	46.43*
							(8.79)	(23.65)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		27.54		26.45	29.23	27.32	27.96	31.28
Adj. R^2	0.14		0.16					
Num. Clusters	54	54	54	54	54	54	54	54
N	738	738	738	738	738	738	738	738

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.10: Robustness. Short-Run Effects of Subsidies on Firm Employment Growth

Dep. Var.:	$\triangle \log Emp_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
asinh(*Credit*)	0.02***	0.12***		0.12***	0.13***	0.13***	0.13***	0.13***
	(0.01)	(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
IV			0.49***					
			(0.16)					
$\log(Emp_{it_0})$	–0.28***	–0.46***	–0.24***	–0.47***	–0.47***	–0.47***	–0.47***	–0.48***
	(0.04)	(0.08)	(0.03)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Chaebol				0.10				0.08
				(0.35)				(0.38)
$\triangle$*Export Demand* $\times$ *Port*					0.09*			0.06
					(0.05)			(0.15)
$\triangle \log$(*Import Tariff*) $\times$ *Port*						–2.15*		–2.20
						(1.24)		(5.72)
$\triangle \log$(*Input Tariff*) $\times$ *Port*							–4.59	1.81
							(3.26)	(18.22)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		26.52		24.05	26.64	25.04	25.96	23.95
Adj. R^2	0.16		0.15					
Num. Clusters	53	53	53	53	53	53	53	53
N	870	870	870	870	870	870	870	870

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is employment growth between 1972 and 1981 or between 1973 and 1982. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Emp_{t_0})$ is log of initial employment in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.11: Long-Run Effects of Subsidies on Firm Employment Growth

Dep. Var.:	$\triangle \log Emp_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$asinh(Credit)$	0.04***	0.11		0.11*	0.12**	0.10	0.10	0.13**
	(0.01)	(0.07)		(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
IV			0.54*					
			(0.32)					
$log(Emp_{it_0})$	–0.59***	–0.68***	–0.54***	–0.70***	–0.70***	–0.67***	–0.67***	–0.70***
	(0.05)	(0.13)	(0.06)	(0.07)	(0.12)	(0.12)	(0.12)	(0.07)
$Chaebol$				0.20				0.12
				(0.86)				(0.84)
$\triangle Export\ Demand \times Port$					0.08			0.38***
					(0.15)			(0.13)
$\triangle \log(Import\ Tariff) \times Port$						1.98		–4.57
						(2.28)		(6.05)
$\triangle \log(Input\ Tariff) \times Port$							5.29	27.17*
							(4.76)	(13.67)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		26.79		25.99	32.91	30.41	31.62	26.71
Adj. R^2	0.37		0.35					
Num. Clusters	54	54	54	54	54	54	54	54
N	873	873	873	873	873	873	873	873

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is employment growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle Export\ Demand \times Port$ is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle Import\ Tariff \times Port$ is the interaction between changes of import tariffs and the port dummy variable. $\triangle Import\ Tariff \times Port$ is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Emp_{t_0})$ is log of initial employment in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.12: Robustness. Short-Run Effects of Subsidies on Firm TFP Growth

Dep. Var.:	$\triangle TFP_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$asinh(Credit)$	0.02***	0.07***		0.07***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
IV			0.51***					
			(0.12)					
$\log(TFP_{it_0})$	–0.72***	–0.74***	–0.71***	–0.74***	–0.74***	–0.74***	–0.74***	–0.74***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Chaebol				0.01				0.02
				(0.20)				(0.19)
$\triangle$*Export Demand* $\times$ *Port*					–0.04			–0.05
					(0.05)			(0.08)
$\triangle\log$(*Import Tariff*) $\times$ *Port*						0.71		2.03
						(1.19)		(6.26)
$\triangle\log$(*Input Tariff*) $\times$ *Port*							1.23	–4.71
							(2.86)	(14.65)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		32.82		26.51	33.30	29.07	31.18	29.00
Adj. R^2	0.60		0.60					
Num. Clusters	50	50	50	50	50	50	50	50
N	595	595	595	595	595	595	595	595

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is TFP growth between 1972 and 1981 or between 1973 and 1982, where TFP is obtained by applying the production function estimation method developed by Ackerberg et al. (2015). The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(TFP_{t_0})$ is log of initial TFP in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.13: Robustness. Long-Run Effects of Subsidies on Firm TFP Growth

Dep. Var.:	$\triangle \log TFP_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$asinh(Credit)$	0.01**	0.21***		0.21***	0.19***	0.20***	0.20***	0.19***
	(0.01)	(0.05)		(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
IV			1.05***					
			(0.14)					
$log(TFP_{it_0})$	–0.75***	–1.04***	–0.77***	–1.03***	–1.03***	–1.04***	–1.0***	–1.01***
	(0.09)	(0.19)	(0.09)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
$Chaebol$				–0.93				–0.83
				(0.63)				(0.53)
$\triangle$*Export Demand* $\times$ *Port*					–0.16			–0.12
					(0.17)			(0.19)
$\triangle \log$(*Import Tariff*) $\times$ *Port*						1.47		–7.69
						(4.28)		(21.75)
$\triangle \log$(*Input Tariff*) $\times$ *Port*							5.63	16.38
							(5.80)	(37.90)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		20.00		19.57	20.21	20.77	20.72	23.13
Adj. R^2	0.91		0.92					
Num. Clusters	54	54	54	54	54	54	54	54
N	683	683	683	683	683	683	683	683

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is TFP growth between 1981 and 2009 or between 1982 and 2010, where TFP is obtained by applying the production function estimation method developed by Ackerberg et al. (2015). The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(TFP_{t_0})$ is log of initial TFP in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.14: Robustness. Alternative Transformation of Credit. Short-Run Effects of Subsidies on Firm Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[Credit > 0]$	1.04***	3.28***		3.24***	3.28***	3.27***	3.25***	3.22***
	(0.21)	(0.65)		(0.65)	(0.66)	(0.66)	(0.66)	(0.61)
IV			0.98***					
			(0.18)					
$\log(Sales_{t_0})$	–0.53***	–0.67***	–0.47***	–0.68***	–0.67***	–0.67***	–0.67***	–0.68***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Chaebol				0.29				0.29
				(0.40)				(0.39)
$\triangle$*Export Demand* $\times$ *Port*				0.29				0.29
				(0.40)				(0.39)
$\triangle \log(\textit{Import Tariff}) \times \textit{Port}$						0.84		–5.06
						(2.32)		(8.67)
$\triangle \log(\textit{Input Tariff}) \times \textit{Port}$							2.88	16.55
							(4.10)	(15.65)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		44.26		42.32	46.88	42.80	44.72	48.59
Adj. R^2	0.45		0.39					
Num. Clusters	56	56	56	56	56	56	56	56
N	764	764	764	764	764	764	764	764

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1972 and 1981 or between 1973 and 1982. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.15: Robustness. Alternative Transformation of Credit. Long-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$1[Credit > 0]$	0.36**	8.84***		8.70***	8.41***	8.69***	8.45***	8.49***
	(0.17)	(2.36)		(2.33)	(2.05)	(2.36)	(2.26)	(2.31)
IV			1.58***					
			(0.17)					
$log(Sales_{it_0})$	–0.13**	–1.01***	–0.13**	–0.93***	–0.97***	–1.00***	–0.98***	–0.91***
	(0.05)	(0.27)	(0.05)	(0.25)	(0.24)	(0.27)	(0.26)	(0.26)
Chaebol				–1.11				–1.06
				(1.41)				(1.23)
$\triangle$*Export Demand* $\times$ *Port*					–0.18			0.18
					(0.25)			(0.31)
$\triangle \log($*Import Tariff*$) \times$ *Port*						6.61		–4.83
						(6.10)		(28.02)
$\triangle \log($*Input Tariff*$) \times$ *Port*							15.39	30.48
							(9.46)	(49.44)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		15.22		15.04	20.64	15.83	17.17	19.03
Adj. R^2	0.15		0.17					
Num. Clusters	54	54	54	54	54	54	54	54
N	738	738	738	738	738	738	738	738

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.16: Robustness. Alternative Transformation of Credits. Short-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1972-1981 and 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(1 + Credit)$	0.06***	0.18***		0.18***	0.18***	0.18***	0.18***	0.18***
	(0.01)	(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
IV			0.98***					
			(0.18)					
$\log(Sales_{t_0})$	–0.53***	–0.68***	–0.47***	–0.69***	–0.68***	–0.68***	–0.67***	–0.69***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Chaebol				0.24				0.25
				(0.40)				(0.38)
$\triangle$*Export Demand* × *Port*					–0.00			0.11
					(0.07)			(0.08)
$\triangle \log($*Import Tariff*$) \times$ *Port*						0.84		–6.26
						(2.18)		(8.70)
$\triangle \log($*Input Tariff*$) \times$ *Port*							3.18	19.54
							(3.82)	(15.90)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		38.99		36.59	41.97	37.72	39.93	42.85
Adj. R^2	0.46		0.39					
Num. Clusters	56	56	56	56	56	56	56	56
N	764	764	764	764	764	764	764	764

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1972 and 1981 or between 1973 and 1982. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* × *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* × *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* × *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.17: Robustness. Alternative Transformation of Credits. Long-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1981-2009 and 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
$\log(1 + Credit)$	0.02**	0.52***		0.51***	0.49***	0.51***	0.50***	0.49***
	(0.01)	(0.14)		(0.14)	(0.12)	(0.14)	(0.13)	(0.13)
IV			1.58***					
			(0.17)					
$log(Sales_{it_0})$	–0.13**	–1.10***	–0.13**	–0.99***	–1.05***	–1.08***	–1.05***	–0.96***
	(0.05)	(0.31)	(0.05)	(0.27)	(0.26)	(0.30)	(0.28)	(0.26)
$Chaebol$				–1.39				–1.32
				(1.53)				(1.32)
$\triangle$*Export Demand* $\times$ *Port*					–0.19			0.22
					(0.26)			(0.30)
$\triangle$ log(*Import Tariff*) $\times$ *Port*						6.32		–10.22
						(5.97)		(27.18)
$\triangle$ log(*Input Tariff*) $\times$ *Port*							16.08	42.69
							(9.84)	(47.59)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		10.74		12.10	14.78	12.93	13.57	13.47
Adj. R^2	0.16		0.19					
Num. Clusters	53	53	53	53	53	53	53	53
N	747	747	747	747	747	747	747	747

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.18: Robustness. Single Long Difference. Short-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1973-1982							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$asinh(Credit)$	0.06***	0.19***		0.19***	0.19***	0.19***	0.18***	0.19***
	(0.01)	(0.04)		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
IV			1.06***					
			(0.20)					
$\log(Sales_{t_0})$	–0.56***	–0.70***	–0.49***	–0.71***	–0.70***	–0.70***	–0.70***	–0.71***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
$Chaebol$				0.25				0.24
				(0.46)				(0.44)
$\triangle Export\ Demand \times Port$					–0.02			0.21*
					(0.08)			(0.12)
$\triangle \log(Import\ Tariff) \times Port$						2.53		–5.37
						(1.99)		(7.95)
$\triangle \log(Input\ Tariff) \times Port$							6.76*	24.69*
							(3.96)	(14.39)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		46.49		47.97	51.13	45.85	47.51	48.28
Adj. R^2	0.49		0.42					
Num. Clusters	43	43	43	43	43	43	43	43
N	396	396	396	396	396	396	396	396

Notes. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1973 and 1982. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2009 or between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle Export\ Demand \times Port$ is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle Import\ Tariff \times Port$ is the interaction between changes of import tariffs and the port dummy variable. $\triangle Import\ Tariff \times Port$ is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1972 or 1973. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.19: Robustness. Single Long Difference. Long-Run Effects of Subsidies on Firms' Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1982-2010							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
asinh(Credit)	0.02*	0.48***		0.48***	0.46***	0.48***	0.47***	0.47***
	(0.01)	(0.13)		(0.14)	(0.12)	(0.13)	(0.12)	(0.13)
IV			1.40***					
			(0.19)					
$\log(Sales_{t_0})$	–0.12*	–1.04***	–0.12	–0.97***	–1.01***	–1.05***	–1.02***	–0.95***
	(0.06)	(0.31)	(0.07)	(0.28)	(0.27)	(0.30)	(0.28)	(0.27)
Chaebol				–1.39				–1.34
				(1.67)				(1.43)
$\triangle$*Export Demand* × *Port*					–0.16			0.29
					(0.25)			(0.27)
$\triangle \log$(*Import Tariff*) × *Port*						6.86		–11.21
						(5.96)		(24.97)
$\triangle \log$(*Input Tariff*) × *Port*							17.00	47.44
							(10.17)	(44.28)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		13.77		13.44	17.46	14.89	16.20	21.10
Adj. R^2	0.07		0.09					
Num. Clusters	46	46	46	46	46	46	46	46
N	401	401	401	401	401	401	401	401

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1982 and 2010. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* × *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* × *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* × *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.20: Robustness. Different Time Horizon. Long-Run Effects of Subsidies on Firm Sales Growth

Dep. Var.:	$\triangle \log Sales_{it}$: 1981-1998 and 1982-1999							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$asinh(Credit)$	0.01**	0.22***		0.22***	0.23***	0.22***	0.22***	0.24***
	(0.01)	(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
IV			0.86***					
			(0.13)					
$\log(Sales_{t_0})$	–0.18***	–0.61***	–0.17***	–0.59***	–0.63***	–0.61***	–0.61***	–0.61***
	(0.04)	(0.15)	(0.05)	(0.13)	(0.14)	(0.15)	(0.15)	(0.11)
$Chaebol$				–0.31				–0.37
				(0.62)				(0.61)
$\triangle$*Export Demand* $\times$ *Port*					0.10			0.16
					(0.13)			(0.21)
$\triangle \log$(*Import Tariff*) $\times$ *Port*						–1.16		–1.86
						(2.87)		(11.42)
$\triangle \log$(*Input Tariff*) $\times$ *Port*							–2.35	6.81
							(4.88)	(18.05)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F		19.82		18.72	27.35	21.07	22.67	26.25
Adj. R^2	0.18		0.19					
Num. Clusters	53	53	53	53	53	53	53	53
N	848	848	848	848	848	848	848	848

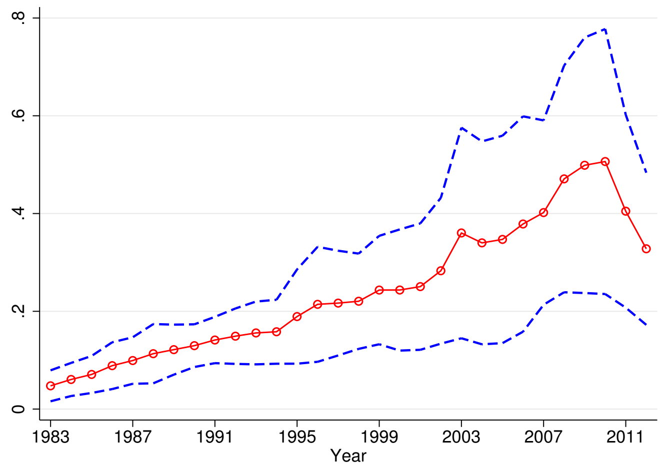
Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 1998 or 1982 and 1999. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle$*Export Demand* $\times$ *Port* is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of import tariffs and the port dummy variable. $\triangle$*Import Tariff* $\times$ *Port* is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Table B.21: Robustness. Different Time Horizon. Long-Run Effects of Subsidies on Firms' Sales Growth

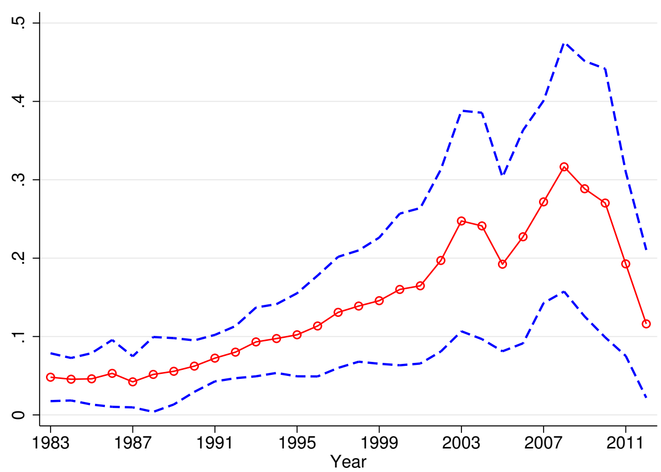
Dep. Var.:	$\triangle \log Sales_{it}$: 1981-2005 and 1982-2006							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$asinh(Credit)$	0.02***	0.35***		0.35***	0.35***	0.35***	0.34***	0.36***
	(0.01)	(0.11)		(0.11)	(0.10)	(0.11)	(0.10)	(0.10)
IV			1.15***					
			(0.12)					
$\log(Sales_{t_0})$	–0.20***	–0.82***	–0.19***	–0.78***	–0.84***	–0.82***	–0.82***	–0.80***
	(0.05)	(0.24)	(0.05)	(0.20)	(0.21)	(0.24)	(0.23)	(0.18)
$Chaebol$				–0.59				–0.65
				(1.17)				(1.08)
$\triangle Export\ Demand \times Port$					0.05			0.26
					(0.21)			(0.28)
$\triangle \log(Import\ Tariff) \times Port$						0.74		–6.58
						(3.84)		(16.36)
$\triangle \log(Input\ Tariff) \times Port$							2.96	25.71
							(7.35)	(26.71)
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
KP-F	10.80		10.66	16.62	12.16	13.26	16.58	
Adj. R^2	0.18		0.19					
Num. Clusters	54	54	54	54	54	54	54	54
N	784	784	784	784	784	784	784	784

Notes. Standard errors clustered at the region level are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS and IV estimates of Equation (2.1). The dependent variable is sales growth between 1981 and 2005 or 1982 and 2006. The OLS estimates are reported in column 1. The IV estimates are reported in columns 2, and 4-8. The IV is defined in (2.3). Column 3 reports the reduced form estimates. Chaebol is a dummy variable which equals 1 if a firm is affiliated with a top 30 Chaebol group. $\triangle Export\ Demand \times Port$ is the interaction between the port dummies with the changes of the world demand shock defined in (2.5). $\triangle Import\ Tariff \times Port$ is the interaction between changes of import tariffs and the port dummy variable. $\triangle Import\ Tariff \times Port$ is the interaction between changes of input tariffs and the port dummy variable, where the input tariffs are defined in (2.7). $\log(Sales_{t_0})$ is log of initial sales in 1981 or 1982. All specifications include region and sector fixed effects. KP-F are the Kleinbergen-Paap F-statistics.

Figure B.6: Yearly Long-Run Estimates



Panel A. log(Sales)



Panel B. TFP

Notes. This figure plots the yearly estimated coefficients of Equation (2.1). In Panel A, the dependent variable is the sales growth between 1982 and the year on the X-axis. In Panel B, the dependent variable is the TFP growth between 1982 and the year on the X-axis, where TFP is obtained by applying the production function estimation method developed by Ackerberg et al. (2015). The blue dashed lines represent the 95% confidence intervals, using standard errors clustered by region.

B.2.1 Additional Placebo Tests

This section provides an additional placebo test, based on data at the regional level. Using population census downloaded from Statistics Korea, we construct manufacturing shares of employment and regional population for each region in 1966, 1970, and 1985. We run the following falsification test:

$$\triangle \log \text{Mfg. Emp. Share}_n = \beta_1 asinh(\text{HCI Credit}_n) + \beta_2 X_n + \epsilon_n$$

where $\triangle \log \text{Mfg. Emp. Share}_n$ is growth of manufacturing employment shares between 1966 and 1970 and between 1970 and 1985. $asinh$(Regional HCI Credits) is the inverse hyperbolic sine transformation of the sum of credits of all HCI sector firms located in region n between 1973 and 1979, that is,

$$\text{HCI Credit}_n = \sum_{f \in \mathcal{F}_{n,HCI}} \sum_{\tau=1973}^{1979} Credit_{f\tau},$$

where $\mathcal{F}_{n,HCI}$ is the set of HCI sector firms located in region n. X_n is a vector of additional controls. By taking the time difference, any time-invariant regional unobservables are differenced out. Robust standard errors are used for inference.

Under our exclusion restriction, we expect that $asinh$(HCI Credits$_n$) is uncorrelated with the growth of manufacturing employment shares between 1966 and 1970. Suppose the Korean government predicted the productivity growth of HCI sectors in the targeted regions. In that case, our estimates may be driven by unobservable productivity growth rather than by the effects of subsidies. If the productivity growth of HCI sectors is persistent, manufacturing employment share growth between 1966 and 1970 may be positively correlated with the sum of all credits of HCI sectors allocated between 1973 and 1979. One caveat of this data set is that we only observe overall manufacturing shares but not employment shares of sub-sectors within the manufacturing sector. Given that the dependent variables are overall manufacturing share growth, if unobservable productivity of non-HCI sector evolved so that it exactly cancels out HCI sector productivity growth, then overall manufacturing shares may remain stable despite productivity growth of HCI sectors. However, setting knife-edge cases aside, as long as changes of unobservable productivity of HCI sectors affect regional manufacturing shares, the falsification test provides additional support for our identifying assumption.

Table B.22: Placebo Test at the Regional Level

Dep. Var.:	$\triangle$ log Mfg. Share: 1966-1970		$\triangle$ log Mfg. Share: 1970-1985	
	(1)	(2)	(3)	(4)
asinh(Regional HCI Loan)	0.01	0.01	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
log of population in 1966		–0.08		–0.17**
		(0.07)		(0.08)
N	61	61	61	61

Notes. Robust standard errors are in parentheses. * p<0.05; ** p<0.01; *** p<0.01. The table reports the OLS estimates of the placebo test at the regional level. In columns 1 and 2, the dependent variable is the log change in regional manufacturing share between 1966 and 1970. In columns 3 and 4, the dependent variable is the log change in regional manufacturing share between 1970 and 1985.

The results are reported in Table B.22. In columns 1 and 2, the dependent variables are manufacturing employment share growth between 1966 and 1970, and in columns 3 and 4, the dependent variables are manufacturing employment share growth between 1970 and 1985. In columns 2 and 4, we additionally control for the log of the total population of 1966. In columns 1 and 2, we find no statistically significant correlation between total credit and manufacturing share growth, supporting our identifying assumption. By contrast, in columns 3 and 4, they are positively correlated, with the coefficient significant at the 5% level

B.3 Theory and Quantification

B.3.1 Optimal Prices When Firms are Not Constrained

If firms are not constrained in the first period, they will charge the price that maximizes the total discounted profits:

$$p_{fj1}^{LBD} = argmax_{p_{fj1}} \Big\{ \Pi_{fj1}(p_{fj1}) + \beta \tilde{\Pi}_{fj2}(p_{fj1}) \Big\},$$

where

$$\Pi_{fj1}(p_{fj1}) = p_{fj1}^{1-\sigma}(P_{j1}^H)^{\sigma-1}X_{j1} - \frac{c_{j1}}{\phi_{fj1}} p_{fj1}^{-\sigma}(P_{j1}^H)^{\sigma-1}X_{j1}$$

and

$$\tilde{\Pi}_{fj2}(p_{fj1}) = \frac{1}{\sigma}\left(\frac{c_{j2}}{\phi_{fj2}}\right)^{1-\sigma}(P_{j2}^H)^{\sigma-1}X_{j2} \times (p_{fj1}^{-\sigma}(P_{j1}^H)X_{j1})^{\xi(\sigma-1)}.$$

P_{fj1}^{LBD} satisfies the following first order condition:

$$\begin{aligned} 0 = (1-\sigma)p_{fj1}^{-\sigma}(P_{j1}^H)^{\sigma-1}X_{j1} + \sigma\frac{c_{j1}}{\phi_{fj1}}p_{fj1}^{-\sigma-1}(P_{j1}^H)^{\sigma-1}X_{j1} \\ - \beta\sigma\xi(\sigma-1)\left[p_{fj1}^{-\sigma\xi(\sigma-1)-1}\Big((P_{j1}^H)^{\sigma-1}X_{j1}\Big)^{\xi(\sigma-1)}\right]\frac{1}{\sigma}\left(\frac{c_{j2}}{\phi_{fj2}}\right)(P_{j2}^H)^{\sigma-1}X_{j2}, \end{aligned}$$

which collapses to the first order condition that maximizes the static profit in the first period when $\xi = 0$.

B.3.2 Equilibrium in the First Period When Firms are Constrained

In this section, we derive expressions for firm-level variables when all firms are constrained in the first period, that is, $\lambda_{j1}/\kappa_{fj1} \leq 1, \forall f$. We first formally show that when $\lambda_{j1}/\kappa_{fj1} \leq 1$ holds, a firm produces at most the quantity that maximizes static profits and charges a higher price than the price that maximizes static profits.

Proposition B.1. *When $\lambda_{j1}/\kappa_{fj1} \leq 1$, firms are constrained, $q_{fj1}^{Friction} \leq q_{fj1}^{Static}$, and $p_{fj1}^{Friction} \geq p_{fj1}^{Static}$, where q_{fj1}^{Static} and p_{fj1}^{Static} are the quantity and price that maximize the static profits.*

Proof. The static profit-maximizing price is

$$p_{fj1}^{Static} = \frac{\sigma}{\sigma - 1} \frac{c_{j1}}{A_{fj1}}$$

and $q_{fj1}^{Static} = (p_{fj1}^{Static})^{-\sigma} (P_{j1}^{H})^{\sigma-1} X_{j1}$. Firms are constrained when

$$\kappa_{fj1} c_{j1} m_{j1} \leq \tilde{\lambda}_{j1} A_{fj1}^{\sigma-1}$$

binds with equality. When charging p_{fj1}^{Static}, total input costs are

$$\begin{aligned}
\kappa_{fj1} c_{j1} m_{fj1} &= \kappa_{fj1} c_{j1} \times \frac{1}{A_{fj1}} (q_{fj1}^{Static}) \\
&= \frac{c_{j1}}{A_{fj1}} (p_{fj1}^{Static})^{-\sigma} (P_{j1}^{H})^{\sigma-1} X_{j1} \\
&= \kappa_{fj1} \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} \\
&\times c_{j1}^{1-\sigma} A_{fj1}^{\sigma-1} (P_{j1}^{H})^{\sigma-1} X_{j1}.
\end{aligned}$$

Combining the two equations above, we can establish that when $\kappa_{fj1}/\lambda_{j1} \leq 1$, firms are constrained. When firms are constrained, their prices are pinned down by the constraints:

$$\begin{aligned}
\kappa_{fj1} c_{j1} m_{fj1} &= \kappa_{fj1} \frac{c_{j1}}{A_{fj1}} q_{fj1}^{Friction} \\
&= \kappa_{fj1} \frac{c_{j1}}{A_{fj1}} (p_{fj1}^{Friction})^{-\sigma} (P_{j1}^{H})^{\sigma-1} X_{j1} \\
&= \lambda_{j1} \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} c_{j1}^{1-\sigma} A_{fj1}^{\sigma-1} (P_{j1}^{H})^{\sigma-1} X_{j1},
\end{aligned}$$

which gives

$$p_{fj1}^{Friction} = \frac{\sigma}{\sigma - 1} \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{-\frac{1}{\sigma}} \frac{c_{j1}}{A_{fj1}}$$

and

$$q_{fj1}^{Friction} = (p_{fj1}^{Friction})^{-\sigma} (P_{j1}^{H})^{\sigma-1} X_{j1}.$$

Because $\lambda_{j1}/\kappa_{fj1} \leq 1$, $p_{fj1}^{Friction} \geq p_{fj1}^{Static}$ and $q_{fjq}^{friction} \leq q_{fj1}^{Static}$ hold. $\square$

We next derive equilibrium allocation when all firms are constrained.

Price. By Proposition B.1

$$p_{fj1}^{Friction} = \frac{\sigma}{\sigma - 1} \frac{c_{j1}}{A_{fj1}} \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{-\frac{1}{\sigma}}.$$

Sales. Demand for firm f's output is $p_{fj1}^{-\sigma}(P_{j1}^H)^{\sigma-1} X_{j1}$. After substituting firm price formula into firm sales $X_{fj1} = p_{fj1} q_{fj1}$, we obtain

$$X_{fj1} = \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\sigma}{\sigma - 1} \frac{c_{j1}}{A_{fj1}} \right)^{1-\sigma} (P_{j1}^H)^{\sigma-1} X_{j1}.$$

Input Expenditures and Total Input Costs. A firm's input expenditures are expressed as

$$\begin{aligned} \left(w_t H_{fj1} + \sum_k P_{k1} M_{fk1} \right) &= c_{j1} m_{fj1} = c_{j1} \frac{q_{fj1}}{A_{fj1}} \\ = \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{-1} \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} &\left(\frac{c_{j1}}{A_{fj1}} \right)^{1-\sigma} (P_{j1}^H)^{\sigma-1} X_{j1} = \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} X_{fj1}. \end{aligned}$$

The first equality comes from a firm's cost minimization such that $w_t H_{fj1} + \sum_k P_{k1} M_{fk1}$ is equal to $c_{j1} m_{fj1}$ where c_{j1} is the price of the input bundle and m_{fj1} is the total quantity of input bundles used by firm f. The second equality comes from a firm's production function. The third equality is derived from the demand curve and prices charged under constraints. Input expenditures on each input sector and on labor are

$$\gamma_j^l \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} X_{fj1}, \qquad l = 1, \ldots, J, \quad H.$$

A firm's total costs on inputs inclusive of subsidies are obtained as

$$\kappa_{fj1} c_{j1} m_{fj1} = \kappa_{fj1} \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} X_{fj1}.$$

Profits. A firm's profits are obtained as sales net of total input costs:

$$\Pi_{fj1} = \left[1 - \kappa_{fj1} \left(\frac{\lambda_{j1}}{\kappa_{fj1}} \right)^{\frac{1}{\sigma}} \left(\frac{\sigma - 1}{\sigma} \right) \right] X_{fj1}.$$

B.3.3 Equilibrium in the Second Period

There is no subsidy and constraint in the second period, so firms maximize their static profits. The firm charges a constant mark-up over marginal cost:

$$p_{fj2} = \frac{\sigma}{\sigma - 1}\frac{c_{j1}}{A_{fj2}},$$

and its sales are

$$X_{fj2} = \left(\frac{\sigma}{\sigma - 1}\frac{c_{j2}}{A_{j2}}\right)^{1-\sigma}(P_{j2}^{H})^{\sigma-1}X_{j2}.$$

Because $A_{fj2} = \phi_{fj2}q_{fj1}^{\xi}$ and $q_{fj1} = p_{fj1}^{-\sigma}(P_{j1}^{H})^{\sigma-1}X_1$, after substituting the firm's first period price, we can rewrite the second period sales as

$$X_{fj2} = \left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{(\sigma-1)\xi}\prod_{h=0}^{1}\left[\left(\frac{\sigma}{\sigma-1}\frac{c_{j,2-h}}{\phi_{fj,2-h}}\right)^{(1-\sigma)(\sigma\xi)^h} \times \left((P_{j,2-h}^{H}\right)^{\sigma-1}X_{j,2-h})^{(\xi(\sigma-1))^h}\right]$$

Because there is no subsidy, the total input expenditures and total input costs are identical in the second period. They are expressed as

$$c_{j2}m_{fj2} = \frac{\sigma - 1}{\sigma}X_{fj2}$$

Profits. Profits in the second period are

$$\Pi_{fj2} = \frac{1}{\sigma}X_{fj2}.$$

B.3.4 Data Construction for the Quantitative Analysis

This section describes the data cleaning procedure for the quantitative analysis. Sectoral import shares and exports are obtained directly from the IO tables. We merge the 1982 firm-level sales to the national IO table for 1983.[2] Let X_{jt}^{IO} denote gross output of sector j, where the superscript reflects the fact that the data come from the IO table. From our firm-balance sheet data, we calculate the sum of sales

[2]The IO table is not available for 1982, so we use the IO table in 1983 instead.

of all firms in sector j: $X_{jt}^{Firm} = \sum_{f\in\mathcal{F}_j} X_{fjt}^{Firm}$, where the superscript $Firm$ is used to denote that the data comes from micro firm-level data. Then, we calculate the residuals as $X_{jt}^{Resid} = X_{jt}^{IO} - X_{jt}^{Firm}$ and take X_{jt}^{Resid} as a separate firm. X_{jt}^{Resid} accounts for the sum of sales of small-sized firms that are not present in our firm-level data. Firm-level sales shares are then obtained as

$$\pi_{fjt} = \frac{X_{fjt}^{Firm}}{X_{jt}^{IO}}$$

for both actual firms in the data and the residual firm.

For some observations, sales are missing, whereas the assets are available for all observations. For observations with missing sales, we impute sales using assets. We run

$$\log Sales_{it} = \beta_1 Assets_{it} + \delta_t + \epsilon_{it}$$

for each sector, where we use cross-sectional variation in assets to predict sales. Then, we use the predicted values as imputed sales.

B.3.5 A Shock Formulation of the Model

This section presents the shock formulation of the model. We express the equilibrium conditions in terms of gross changes $\hat{x} = x^c/x$ where x^c and x are the counterfactual and pre-shock allocations. In the short-run hat algebra, the shocks are $\hat{\kappa}_{fj1}$, and in the long-run hat algebra, the shocks are $\hat{A}_{fj2}^{L}$.

Short-Run. In the short-run counterfactual, λ_{j1}, P_{j1}^F, D_{j1}^F, and ϕ_{fj1} remain constant, but only κ_{fj1} are changed. We set $\hat{\lambda}_{j1}^S = 1$, $\hat{A}_{fj1}^S = 1$, $\hat{P}_{j1}^{F,S} = 1$, $\hat{D}_{j1}^{F,S} = 1$, $\hat{H}_1^S = 1$, and $\hat{\kappa}_{fj1}^S = \kappa_{c,fj1}/\kappa_{fj1}$, where $\kappa_{c,fj1} = 1$.

A firm's price changes are written as

$$\hat{p}_{fj1}^S = \left(\frac{\hat{\lambda}_{j1}^S}{\hat{\kappa}_{fj1}^S}\right)^{-\frac{1}{\sigma}} \frac{\hat{c}_{j1}^S}{\hat{A}_{fj1}^S}.$$

Changes of Home sectoral price indices are

$$(\hat{P}_{j1}^{H,S})^{1-\sigma} = \sum_{f \in \mathcal{F}_j} \pi_{fj1} (\hat{p}_{fj1}^S)^{1-\sigma}.$$

Changes of final price indices are

$$(\hat{P}_{j1}^S)^{1-\rho} = (1-\pi_{j1}^F)(\hat{P}_{j1}^{F,S})^{1-\rho} + \pi_{j1}^F (\hat{P}_{j1}^{H,S})^{1-\rho}.$$

A firm's counterfactual market share is

$$\pi_{c,fj1} = \frac{(\hat{p}_{fj1}^S)^{1-\sigma}\pi_{fj1}}{\sum_{f' \in \mathcal{F}_j} (\hat{p}_{f'j1}^S)^{1-\sigma}\pi_{f'j1}}.$$

A counterfactual import share is

$$\pi_{c,j1}^F = \frac{(\hat{P}_{j1}^{F,S})^{1-\rho}\pi_{j1}^F}{(\hat{P}_{j1}^{H,S})^{1-\rho}(1-\pi_{j1}^F) + (\hat{P}_{j1}^{F,S})^{1-\rho}\pi_{j1}^F}$$

Counterfactual exports are

$$EX_{c,j1} = (\hat{c}_{j1}^S)^{1-\rho} \hat{D}_{j1}^F EX_{j1}$$

Labor market clearing can be written as

$$\hat{w}_1^S \hat{H}_1^S w_1 H_1 = \frac{\sigma-1}{\sigma} \sum_{j \in \mathcal{J}_M} \gamma_j^H X_{c,j1} + \sum_{j \in \mathcal{J}_{NM}} \gamma_j^H X_{c,j1},$$

where

$$w_1 H_1 = \frac{\sigma-1}{\sigma} \sum_{j \in \mathcal{J}_M} \gamma_j^H X_{j1} + \sum_{j \in \mathcal{J}_{NM}} \gamma_j^H X_{j1}$$

Goods market clearing is expressed as

$$\begin{aligned} X_{c,j1} &= (1-\pi_{c,j1}^F) \\ &\times \left[\alpha^j (\hat{w}_1^S \hat{H}_1^S w_1 H_1 + \Pi_{c,1} + T_{c,1}) + \frac{\sigma-1}{\sigma} \sum_{k \in \mathcal{J}_M} \gamma_k^j X_{c,k1} + \sum_{k \in \mathcal{J}_{NM}} \gamma_k^j X_{c,k1}\right] + EX_{c,j1} \end{aligned}$$

Firms' sales and profits are expressed as

$$X_{c,fj1} = \pi_{c,fj1} X_{c,j1},$$

and

$$\pi_{c,fj1} = \left[1 - \kappa_{c,fj1}\left(\frac{\lambda_{j1}}{\kappa_{c,fj1}}\right)^{\frac{1}{\sigma}}\frac{\sigma-1}{\sigma}\right]X_{c,fj1}.$$

Aggregate profits are

$$\Pi_{c,1} = \sum_{j\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_j}\Pi_{c,fj1}.$$

Lump-sum transfers are

$$T_{c,1} = \frac{\sigma-1}{\sigma}\sum_{j\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_j}(\kappa_{c,fj1}-1)\left(\frac{\lambda_{j1}}{\kappa_{c,fj1}}X_{c,fj1}\right).$$

The Long Run. In the long-run hat algebra, there are four exogenous changes: $\hat{H}_2^L$, $\hat{A}_{fj2}^L$, $\hat{\kappa}_{fj2}^L$, $\hat{\lambda}_{j2}^L$. In the second period, there are no subsidy and no constraints, so we set $\kappa_{fj2} = 1$ and $\lambda_{j2} = 1$. Then, the long-run changes of subsidies and constraints are given as $\hat{\kappa}_{fj2}^L = 1/\kappa_{fj1}$ and $\hat{\lambda}_{j2}^L = 1/\lambda_{j1}$.

The long-run counterfactual productivity changes are computed as

$$\hat{A}_{c,fj2}^L = \left(\frac{A_{f_0j2}}{A_{f_0j1}}\right)\times\left(\frac{A_{fj2}/A_{f_0j2}}{A_{fj1}/A_{f_0j1}}\right)\times(\hat{q}_{c,fj1}^S)^{\xi}$$

where $\frac{A_{fj2}/A_{f_0j2}}{A_{fj1}/A_{f_0j1}}$ is obtained directly from the data, $\frac{A_{f_0j2}}{A_{f_0j1}}$ is internally calibrated data by exactly fitting the data, and $\hat{q}_{c,fj1}^S$ is obtained from the short-run hat algebra.

A firm's price changes and market shares are written as

$$\hat{p}_{fj2}^L = \left(\frac{\hat{\lambda}_{j2}^L}{\hat{\kappa}_{fj2}^L}\right)^{-\frac{1}{\sigma}}\frac{\hat{c}_{j2}^L}{\hat{A}_{c,fj2}^L},$$

and

$$\pi_{fj2} = \frac{(\hat{p}_{fj2}^L)^{1-\sigma}\pi_{fj1}}{\sum_{f'\in\mathcal{F}_j}(\hat{p}_{f'j2}^L)^{1-\sigma}\pi_{f'j1}}.$$

Changes of Home sectoral price indices are

$$(\hat{P}_{j2}^{H,L})^{1-\sigma} = \sum_{f\in\mathcal{F}_j}\pi_{fj1}(\hat{p}_{fj2}^L)^{1-\sigma}.$$

Changes of final price indices are

$$(\hat{P}_{j2}^{L})^{1-\rho} = (1-\pi_{j1}^{F})(\hat{P}_{j2}^{F,L})^{1-\rho} + \pi_{j1}^{F}(\hat{P}_{j2}^{H,L})^{1-\rho}.$$

Import shares are

$$\pi_{j2}^{F} = \frac{(\hat{P}_{j2}^{F,L})^{1-\rho}\pi_{j1}^{F}}{(\hat{P}_{j2}^{H,L})^{1-\rho}(1-\pi_{j1}^{F}) + (\hat{P}_{j2}^{F,L})^{1-\rho}\pi_{j1}^{F}}.$$

Exports are

$$EX_{j2} = (\hat{c}_{j2}^{L})^{1-\rho}\hat{D}_{j2}^{F,L}EX_{j1}$$

Labor market clearing can be written as

$$\hat{w}_2^L \hat{H}_2^L w_1 H_1 = \frac{\sigma-1}{\sigma}\sum_{j\in\mathcal{J}_M}\gamma_j^H X_{j2} + \sum_{j\in\mathcal{J}_{NM}}\gamma_j^H X_{j2},$$

where

$$w_1 H_1 = \frac{\sigma-1}{\sigma}\sum_{j\in\mathcal{J}_M}\gamma_j^H X_{j1} + \sum_{j\in\mathcal{J}_{NM}}\gamma_j^H X_{j1}$$

Goods market clearing is expressed as

$$X_{c,j2} = (1-\pi_{c,j2}^{F})\times \left[\alpha^j(\hat{w}_2^L \hat{H}_2^L w_1 H_1 + \Pi_2 + T_2) + \frac{\sigma-1}{\sigma}\sum_{k\in\mathcal{J}_M}\gamma_k^j X_{k2} + \sum_{k\in\mathcal{J}_{NM}}\gamma_k^j X_{k2}\right] + EX_{c,j2}.$$

Firms' sales and profits are expressed as

$$X_{fj2} = \pi_{fj2}X_{j2},$$

and

$$\Pi_{fj2} = \frac{1}{\sigma}X_{fj2}.$$

Aggregate profits are

$$\Pi_2 = \sum_{j\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_j}\Pi_{fj2}.$$

Lump-sum transfers are

$$T_2 = 0.$$

B.3.6 Model Solution and Algorithm

To solve the model, we require the following information.

Pre-shock data values in 1982. The data values in 1982 correspond to the first period in the model:

- Gross sales of firms in the manufacturing sectors, $\forall f \in \mathcal{F}_j$ and $\forall j \in \mathcal{J}_M$
- Gross sales of sector j. For $j \in \mathcal{J}$, $X_{j1} = \sum_{f \in \mathcal{F}_j} X_{fj1}$
- Sectoral import shares π_{j1}^F
- Sectoral export values EX_{j1}^F

Shocks.

- Levels of $\{\lambda_{j1}\}$ in the first period, $\forall j \in \mathcal{J}_M$. In the second period, no firms are constrained, i.e. $\lambda_{j2} = 1$, $\forall j$
- Subsidy level in the first period κ_{fj1}, $\forall j \in \mathcal{J}_M$. In the second, there is no subsidy, i.e., $\kappa_{fj2} = 1$, $\forall f, j$
- Long-run productivity changes of firms in the manufacturing sectors, $\{\hat{A}_{fj2}^L\}$, $\forall f \in \mathcal{F}_j$ and $\forall j \in \mathcal{J}_M$. For the non-manufacturing sectors, there is a representative firm in each sector, so we only require sectoral long-run productivity changes $\{\hat{A}_{j2}^L\}$, $\forall j \in \mathcal{J}_{NM}$.
- Long-run Foreign demand shocks $\{\hat{D}_{j2}^{F,L}\}$
- Long-run Foreign import price shocks $\{\hat{P}_{j2}^{F,L}\}$

Parameters.

- The elasticity of substitution σ and ρ
- The learning-by-doing parameter ξ
- Final consumption shares α^j, $\forall j \in \mathcal{J}$

- Production parameters γ_j^H and γ_j^k, $\forall j, k \in \mathcal{J}$

Model Algorithm. Given the values of the parameters, the shocks and the data values in 1982, the model is solved using the following algorithm

- Step 1: Apply short-run hat algebra to the pre-shock data values in 1982
  1. Feed in $\hat{\kappa}_{fj1}^S$
  2. Solve for the short-run equilibrium.
  3. Calculate counterfactual equilibrium allocation.
- Step 2: Construct the counterfactual long-run productivity changes
  1. From Step 1, calculate the counterfactual changes of quantity produced
  $$\hat{q}_{c,fj1}^S = \hat{p}_{c,fj1}^S (\hat{P}_{c,j1}^{H,S})^{\sigma-1} \hat{X}_{c,j1}^S$$
  2. Calculate $\hat{A}_{c,fj2}^L = \hat{A}_{fj2}^L \times \hat{q}_{c,fj1}^S$ where $\hat{A}_{fj2}^L$ is backed out from the data.
- Step 3: Long-run hat algebra to the pre-shock data values in 1982
  1. Feed in six shocks: $\hat{A}_{fj2}^L$, $\hat{D}_{j2}^{F,L}$, $\hat{P}_{j2}^{F,L}$, $\lambda_{j2} = 1$, $\kappa_{fj2} = 1$, and $\hat{H}_2^L$ to the baseline (pre-shock) data values
  2. Obtain long-run equilibrium allocation changes.
  3. Calculate the long-run real income changes $\hat{y}_2^L / \hat{P}_2^L$
- Step 4: Long-run hat algebra to the counterfactual data values in 1982
  1. Feed in six shocks: $\hat{A}_{fj2}^L$, $\hat{D}_{j2}^{F,L}$, $\hat{P}_{j2}^{F,L}$, $\lambda_{j2} = 1$, $\kappa_{fj2} = 1$, and $\hat{H}_2^L$ to the counterfactual data values in 1982
  2. Obtain long-run equilibrium allocation changes under counterfactual.
  3. Calculate the long-run real income changes $\hat{y}_{c,2}^L / \hat{P}_{c,2}^L$ under counterfactual
- Step 5: Calculate welfare changes under counterfactual

1. Based on the results obtained under steps 1-4, calculate the following welfare changes under the counterfactual

$$U_c/U = \left(\frac{\hat{y}_1^S}{\hat{P}_1^S}\right)\left(\frac{\tilde{y}_2^L}{\tilde{P}_2^L}\frac{\hat{y}_1^S}{\hat{P}_1^S}\right)^{\beta}$$

where

$$\frac{\tilde{y}_2^L}{\tilde{P}_2^L} = \frac{\hat{y}_{c,2}^L}{\hat{P}_{c,2}^L}\Bigg/\frac{\hat{y}_2^L}{\hat{P}_2^L}$$

and $\hat{y}_1^S/\hat{P}_1^S$ is obtained from the short-run hat algebra applied to the baseline (pre-shock) data values in 1982, $\hat{y}_2^L/\hat{P}_2^L$ is obtained from the long-run hat algebra applied to the baseline (pre-shock) data values in 1982, and $\hat{y}_{c,2}^L/\hat{P}_{c,2}^L$ is obtained from the long-run hat algebra applied to the counterfactual data values in 1982.

B.3.7 Backing Out the Long-Run Shocks

To implement the long-run hat algebra, we have to compute the long-run shocks $\{\hat{A}_{f_0j2}^L, \hat{D}_{j2}^{F,L}, \hat{P}_{j2}^{F,L}\}$, which has $3 \times J$ dimension. We compute these shocks by exactly matching the model to the observed data on changes of producer price indices, import shares, and exports between 1983 and 2010. Import shares and exports are obtained from the IO tables. Producer price indices are obtained from the OECD Stan database. When fitting the price changes, we normalize price changes across sectors by price change of one sector, which pins down $\hat{A}_{f_0j2}^L$ relative to the reference sector. Without loss of generality, we use the first sector (Food, Beverages, & Tobacco) as our reference sector ($j = 1$). Then, we use real output changes of the reference sector to pin down $\hat{A}_{f_0j2}^L$ of the reference sector.

We compute these shocks using the following algorithm:

- Step 1: Guess $\{\hat{A}_{f_0j2}^{L,0}, D_{j2}^{F,L,0}, P_{j2}^{F,L,0}\}$

- Step 2: Compute the firm-level long-run productivity shock based on the guess:

$$A^{L,0}_{fj2} = \hat{A}^{L,0}_{f_0j2} \times \underbrace{\left(\frac{A_{fj2}/A_{f_0j2}}{A_{fj1}/A_{f_0j1}}\right)}_{\text{Data}}.$$

  The changes of relative productivity is taken directly from the data.

- Step 3: Given the guess, compute prices.

- Step 4: Update $\hat{P}^{F,L,0}_{j2}$ and observed import share changes between 1982 and 2010.

- Step 5: Update $\hat{D}^{F,L,0}_{j2}$ using and observed exports changes between 1982 and 2010.

- Step 6: Compute price changes. Update $\hat{A}^{L,0}_{f_0j2}$ for $j = 2, \ldots, J$ until $\hat{P}_{jt}/\hat{P}_{1t}$ fits the PPI changes relative to the reference sector ($j = 1$).

- Step 7: Update $\hat{A}^{L,0}_{f_0j2}$ for $j = 1$ until $\hat{X}^{L}_{jt}/\hat{P}^{L}_{jt}$ fits the real output changes of the data.

- Step 8: Iterate Steps 2-7 until the convergence.

B.3.8 Satisfying Market Clearing

We require the market-clearing conditions in levels to be satisfied in the first and second periods to apply the hat algebra and to back out the shocks. Given $\{\kappa_{fj1}\}$ and $\{\lambda_{j1}\}$, in the first period, firm-level sales $\{X_{fj1}\}$ and industry-level gross outputs

$\{X_{j1}\}$, exports $\{EX_{j1}\}$, and import shares $\{\pi_{j1}^{im}\}$ should satisfy

$$
\begin{aligned}
X_{fj1} = \pi_{fj1}(1-\pi_{j1}^{im}) \Bigg[\alpha^j \Bigg\{ & \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \gamma_k^H \left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}} \left(\frac{\sigma-1}{\sigma}\right) X_{fk1} + \sum_{k\in\mathcal{J}_{NM}} \gamma_j^H X_{k1}}_{w_1 H_1} \\
& + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \left(1-\kappa_{fk1}\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\right) X_{fk1}}_{=\Pi_1} \\
& + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_j} (\kappa_{fk1}-1)\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right) X_{fk1}}_{=T_1} \Bigg\} \\
& + \sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \gamma_k^j \left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{\frac{1}{\sigma}} \frac{\sigma-1}{\sigma} X_{fk1} \\
& + \sum_{k\in\mathcal{J}_M} \gamma_k^j X_{k1} \Bigg] \\
& + \pi_{fj1} EX_{j1}, \quad \forall f, j.
\end{aligned}
$$

Similarly, in the second period, the following equation should be satisfied:

$$
\begin{aligned}
X_{fj2} = \pi_{fj2}(1-\pi_{j2}^{im}) \times & \\
& \Bigg[\alpha^j \Bigg\{ \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \gamma_k^H \left(\frac{\sigma-1}{\sigma}\right) X_{fk2} + \sum_{k\in\mathcal{J}_{NM}} \gamma_j^H X_{k2}}_{w_2 H_2} + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \frac{1}{\sigma} X_{fk2}}_{=\Pi_2} \Bigg\} \\
& + \sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k} \gamma_k^j \frac{\sigma-1}{\sigma} X_{fk1} + \sum_{k\in\mathcal{J}_M} \gamma_k^j X_{k2} \Bigg] + \pi_{fj2} EX_{j2}, \quad \forall f, j.
\end{aligned}
$$

In the data, these conditions are unlikely to hold. Therefore, following Costinot and Rodríguez-Clare (2014) and di Giovanni et al. (2020), we introduce sector-specific wedge $\{\zeta_{jt}\}$ that makes the above market clearing condition to hold exactly, that is,

$$
\begin{aligned}
X_{fj1} = \pi_{fj1}(1-\pi^{im}_{j1})\times \\
\Bigg[\alpha^j \Bigg\{ & \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^H_k\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)X_{fk1}+\sum_{k\in\mathcal{J}_{NM}}\gamma^H_j X_{k1}}_{w_1H_1} \\
& + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\left(1-\kappa_{fk1}\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\right)X_{fk1}}_{=\Pi_1} \\
& + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_j}(\kappa_{fk1}-1)\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)X_{fk1}}_{=T_1}\Bigg\} \\
& + \sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^j_k\left(\frac{\lambda_{j1}}{\kappa_{fj1}}\right)^{\frac{1}{\sigma}}\frac{\sigma-1}{\sigma}X_{fk1}+\sum_{k\in\mathcal{J}_M}\gamma^j_k X_{k1}\Bigg] \\
& + \pi_{fj1}EX_{j1}+\zeta_{j1}, \quad \forall f,j,
\end{aligned}
$$

and

$$
\begin{aligned}
X_{fj2} = \pi_{fj2}(1-\pi^{im}_{j2}) \\
\times\Bigg[\alpha^j\Bigg\{ & \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^H_k\left(\frac{\sigma-1}{\sigma}\right)X_{fk2}+\sum_{k\in\mathcal{J}_{NM}}\gamma^H_j X_{k2}}_{w_2H_2} \\
& + \underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\frac{1}{\sigma}X_{fk2}}_{=\Pi_2}\Bigg\} \\
& + \sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^j_k\frac{\sigma-1}{\sigma}X_{fk1}+\sum_{k\in\mathcal{J}_M}\gamma^j_k X_{k2}\Bigg] + \pi_{fj2}EX_{j2}+\zeta_{j2}, \quad \forall f,j.
\end{aligned}
$$

Then we apply the hat algebra and then feed the shocks $\hat{\zeta}^S_{jt}=0, \forall j,t$ that eliminate the wedges. Other shocks are held constant. We obtain $\{\hat{X}^S_{fjt}\}$ and $\{\hat{X}^S_{jt}\}$ by solving

$$
\begin{aligned}
\hat{X}^S_{fj1}X_{fj1} &= \hat{\pi}^S_{fj1}\pi_{fj1}(1-\hat{\pi}^{im,S}_{j1}\pi^{im}_{j1}) \\
&\times\Bigg[\alpha^j\Bigg\{\underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^H_k\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\hat{X}^S_{fk1}X_{fk1}+\sum_{k\in\mathcal{J}_{NM}}\gamma^H_j\hat{X}^S_{k1}X_{k1}}_{\hat{w}^S_1 w_1 H_1} \\
&\quad+\underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\left(1-\kappa_{fk1}\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\right)\hat{X}^S_{fk1}X_{fk1}}_{=\hat{\Pi}^S_1\Pi_1} \\
&\quad+\underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}(\kappa_{fk1}-1)\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\left(\frac{\sigma-1}{\sigma}\right)\hat{X}^S_{fk1}X_{fk1}}_{=\hat{T}^S_1 T_1}\Bigg\} \\
&\quad+\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^j_k\left(\frac{\lambda_{k1}}{\kappa_{fk1}}\right)^{\frac{1}{\sigma}}\frac{\sigma-1}{\sigma}\hat{X}^S_{fk1}X_{fk1}+\sum_{k\in\mathcal{J}_M}\gamma^j_k\hat{X}^S_{k1}X_{k1}\Bigg] \\
&\quad+\hat{\pi}^S_{fj1}\pi_{fj1}\hat{EX}^S_{j1}EX_{j1}+\hat{\zeta}^S_{j1}\zeta_{j1}, \quad \forall f,j,
\end{aligned}
$$

and

$$
\begin{aligned}
\hat{X}^S_{fj2}X_{fj2} &= \hat{\pi}^S_{fj2}\pi_{fj2}(1-\hat{\pi}^{im,S}_{j2}\pi^{im}_{j2}) \\
&\times\Bigg[\alpha^j\Bigg\{\underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^H_k\left(\frac{\sigma-1}{\sigma}\right)\hat{X}^S_{fk2}X_{fk2}+\sum_{k\in\mathcal{J}_{NM}}\gamma^H_j\hat{X}^S_{k2}X_{k2}}_{\hat{w}^S_2 w_2 H_2} \\
&\quad+\underbrace{\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\frac{1}{\sigma}\hat{X}^S_{fk2}X_{fk2}}_{=\hat{\Pi}^S_2\Pi_2}\Bigg\} \\
&\quad+\sum_{k\in\mathcal{J}_M}\sum_{f\in\mathcal{F}_k}\gamma^j_k\frac{\sigma-1}{\sigma}\hat{X}^S_{fk1}X_{fk1} \\
&\quad+\sum_{k\in\mathcal{J}_M}\gamma^j_k\hat{X}^S_{k2}X_{k2}\Bigg] \\
&\quad+\hat{\pi}^S_{fj2}\pi_{fj2}\hat{EX}^S_{j2}EX_{j2}+\hat{\zeta}^S_{j2}\zeta_{j2}, \quad \forall f,j.
\end{aligned}
$$

After solving for $\{\hat{X}^S_{fjt}\}$, $\{\hat{X}^S_{jt}\}$, $\{\hat{EX}^S_{jt}\}$, and $\{\hat{\pi}^{im,S}_{j1}\}$, we obtain the new $\{X^S_{fjt}\}$,

$\{X_{jt}^S\}$, $\{EX_{jt}^S\}$, and $\{\pi_{j1}^{im,S}\}$ that satisfy the market clearing conditions. We use the new set of $\{X_{fjt}^S\}$, $\{X_{jt}^S\}$, $\{EX_{jt}^S\}$, and $\{\pi_{j1}^{im,S}\}$ as our main data for the counterfactual analysis.

B.3.9 Construction of Predicted Subsidies

1. Using the first stage estimates of the baseline specification (column 1 of Table B.4), we calculate predicted subsidies as

$$asin\widehat{h(Credit_f)} = \hat{\beta}_1 IV + \hat{\beta}_2 \log(Sale_{ft_0}) + \hat{\delta}_n + \hat{\delta}_j,$$

   where we set $t_0 = 1973$. This corresponds to the second set of long-difference of our empirical analysis.

   - Note that our regression only includes continuing firms between 1973 and 1982. For firms that entered between 1973 and 1982, we cannot observe initial sales. For these entering firms, we impute these missing initial sales using the mean other continuing firms.
   - The region fixed effects (δ_n) of some regions are missing if there are no continuing firms or only one firm in these regions in 1973.

2. We normalize predicted subsidies $asin\widehat{h(Credit_f)}$ so that the firm with the minimum amounts of the predicted subsidies receives zero amounts of credits: $asin\widehat{h(Credit_f)} + \min_{f' \in \mathcal{F}}\{asin\widehat{h(Credit_{f'})}\}$.

3. We normalize these predicted subsidies so that the sum of the predicted subsidies to be the same with the sum of the actual subsidies of the data.

4. Calculate the subsidy rate using the short-run estimates.

5. Once we obtain the subsidy rate based on the predicted subsidies, we conduct the same analysis with the baseline. We also use the same calibrated values of

the structural parameters with the baseline. This proceeds as follows:

- Make the data satisfy the market clearing conditions as in Section B.3.8.
- Back out the long-run shocks as in Section B.3.7.
- Conduct the short-run and long-run hat algebra.

B.3.10 Robustness

Table B.23: Robustness. Elasticity of Substitution

σ	ρ	β	Welfare loss (%)		
			Total	Short-run	Long-run
(1)	(2)	(3)	(4)	(5)	(6)
3	2	0.9	−16.46	−1.15	−15.31
3	2	1.62	−28.7	−1.15	−27.55
3	3	0.9	−20.96	−3.58	−17.38
3	3	1.62	−34.86	−3.58	−31.28
4	2	0.9	−7.72	1.07	−8.79
4	2	1.62	−14.74	1.07	−15.81
4	3	0.9	−9.95	−0.84	−9.11
4	3	1.62	−17.24	−0.84	−16.4
4	4	0.9	−11.57	−1.94	−9.63
4	4	1.62	−19.27	−1.94	−17.33

Notes. The table reports the welfare effects under the counterfactual in which the Korean government did not conduct the industrial policy. The rows differ in the elastities of substitition σ and ρ and in the values of β, where $\beta = 1.62$ corresponds to the assumption of a permanent technology improvement, and $\beta = 0.9$ to a temporary one.

APPENDIX C

Appendices to Chapter 3

C.1 Construction of Data

Balance Sheet Data. Firms' balance sheet data comes from Compustat. The empirical analysis excludes:

1. Firms in industries other than manufacturing (SIC $\notin [20, 40]$).
2. Firms that are not incorporated in the US.
3. Firm-year observations whose employment, capital, or sales data are missing or below zero.
4. Firm-year observations with negative values of employment, capital, or sales.
5. Firm-year observations with top and bottom 0.5% of MRPL: I drop these outlier samples not to make my results be driven by outliers following Hsieh and Klenow (2009).

Lobbying Data. Lobbying data became publicly disclosed since LDA (1995). Lobbyists have to report summaries of their lobbying activities semi-annually from 1998 to 2007 and quarterly after 2007. The Center for Responsive Politics constructed the lobbying database based on these reports. I downloaded lobbying data from the Center for Responsive Politics. According to the LDA (1995), the lobbying activities are lobbying contacts and efforts in support of such contacts, including preparation and planning activities, research, and other background work that is intended, at the time it is performed, for use in contacts and coordination with the lobbying activities of others.

An example of the lobbying reports by lobbyists are displayed in Figure C.1 and C.2. This is the report by the lobbyists whose client was Apple Inc in the third quarter of 2020. In Figure C.1, the total lobbying expenditure is reported. In Figure C.2, general issue area code is reported. I use these issue area codes to construct the non-trade-related lobbying expenditures. In this example, Apple Inc lobbied for tax-related issues.

Trade Data. Sector-level trade data come from Comtrade. I covert HS 6-digit to SIC 4-digit using the conversion from Pierce and Schott (2012) and Acemoglu et al. (2016).

Industry-Level Data. Industry-level data comes from NBER-CES manufacturing data. The NBER-CES manufacturing data has detailed information on industry-level variables at SIC 4-digit code, such as gross output or value-added. Using the gross output data, I construct domestic absorption with imports and exports data from Comtrade. I also obtain value-added shares at the industry level by dividing value-added by gross output.

Congressional Committee Assignment. I obtain congressional committee assignment data from Stewart and Woon (2017).

Wage Data. I obtain 3-digit SIC industry-level wage data within each state from the Census of Business Pattern. I convert the 3-digit NAICS codes to the 3-digit SIC code. The constructed wage data is then matched with the firm-level data based on firms' headquarter locations and industry affiliation.

State-Level Tax. I obtain state-level tax data from the Panel Database on Incentives and Taxes (PDIT) database (Bartik, 2018). It has detailed information on corporate income tax, job creation tax credit, investment tax credit, R&D tax credit, and property tax abatement. These variables are used as controls in Equation 3.13.

Effective Tax Rates. The cash effective tax rates (ETR) developed by Dyreng et al. (2008) is defined as

$$ETR_{it} = \frac{\sum_{h=1}^{6} TXPD_{i,t-h}}{\sum_{h=1}^{6}(PI_{i,t-h} - SPI_{i,t-h})},$$

where $TXPD$ is cash tax paid (Item 317), PI is pretax income (Item 122) and SPI is special itesm (Item 12) from Compustat

Following Dyreng et al. (2017) and Hanlon and Slemrod (2009),

1. samples should have non-missing and non-negative values of TXPD, PI, and SPI.

2. if ETR is larger than 0.5, I reset them to 0.5 to reduce the effect of outlier samples.

I average each variable over six years and calculate the long-run ETR. It is shown in Dyreng et al. (2008) that the long-run average is more reliable. ETR is used as an alternative dependent variable in Equation 3.13.

Name-Matching. I matched firm names in Compustat to parent firm names in the lobbying database. The matching step is described as follows. The matching is done year by year.

- Step 1: Match firm name based on their exact name without any modifications.
- Step 2: For the names not matched in the step 1, unify abbreviations and then match the remaining names. For example, “Incorporated” is converted into “INC.”
- Step 3: For the names not matched in the step 2, Match a firm’s name after dropping out abbreviations.
- Step 4: For the names not matched in the step 3, I use the fuzz-name matching algorithm. I calculate the fuzz ratio that measures the similarity between two different names with the fuzz-name matching algorithm. I keep the matched pair if their fuzz ratio is above 95 and the name is composed of more than 20 letters. These two criteria increase the accuracy of matching.

1/31/2021 LD-2 Disclosure Form

Clerk of the House of Representatives Legislative Resource Center 135 Cannon Building Washington, DC 20515 http://lobbyingdisclosure.house.gov	Secretary of the Senate Office of Public Records 232 Hart Building Washington, DC 20510 http://www.senate.gov/lobby

LOBBYING REPORT

Lobbying Disclosure Act of 1995 (Section 5) - **All Filers Are Required to Complete This Page**

1. Registrant Name ☑ Organization/Lobbying Firm ☐ Self Employed Individual
The Glover Park Group LLC

2. Address
Address1 1025 F Street NW Address2 9th Floor
City Washington State DC Zip Code 20004 Country USA

3. Principal place of business (if different than line 2)
City State Zip Code Country

4a. Contact Name Mr. Joel Johnson b. Telephone Number 2023370808 c. E-mail jjohnson@gpg.com

5. Senate ID# 86196-1005700

7. Client Name ☐ *Self* ☐ *Check if client is a state or local government or instrumentality*
Apple, Inc.

6. House ID# 365480113

TYPE OF REPORT 8. Year 2020 Q1 (1/1 - 3/31) ☐ Q2 (4/1 - 6/30) ☐ Q3 (7/1 - 9/30) ☑ Q4 (10/1 - 12/31) ☐

9. Check if this filing amends a previously filed version of this report ☐

10. Check if this is a Termination Report ☐ Termination Date ________ 11. No Lobbying Issue Activity ☐

INCOME OR EXPENSES - YOU MUST complete either Line 12 or Line 13

12. Lobbying	**13. Organizations**
INCOME relating to lobbying activities for this reporting period was:	**EXPENSE** relating to lobbying activities for this reporting period were:
Less than $5,000 ☐	Less than $5,000 ☐
$5,000 or more ☑ $ 40,000.00	$5,000 or more ☐ $ ______
Provide a good faith estimate, rounded to the nearest $10,000, of all lobbying related income for the client (including all payments to the registrant by any other entity for lobbying activities on behalf of the client).	**14. REPORTING** Check box to indicate expense accounting method. See instructions for description of options. ☐ **Method A.** Reporting amounts using LDA definitions only ☐ **Method B.** Reporting amounts under section 6033(b)(8) of the Internal Revenue Code ☐ **Method C.** Reporting amounts under section 162(e) of the Internal Revenue Code

Signature Digitally Signed By: Nicole Dade **Date** 10/19/2020 11:22:17 AM

https://lda.senate.gov/filings/public/filing/2fb2ab27-82ed-4c80-abe4-b74f0cbdadad/print/ 1/6

Figure C.1: The Lobbying Report by Apple Inc in 2020, Total Lobbying Expenditure

LOBBYING ACTIVITY. Select as many codes as necessary to reflect the general issue areas in which the registrant engaged in lobbying on behalf of the client during the reporting period. Using a separate page for each code, provide information as requested. Add additional page(s) as needed.

15. General issue area code TAX

16. Specific lobbying issues

Issues related to tax, trade, technology and broadband.

17. House(s) of Congress and Federal agencies ☐ Check if None

U.S. SENATE, U.S. HOUSE OF REPRESENTATIVES

18. Name of each individual who acted as a lobbyist in this issue area

First Name	Last Name	Suffix	Covered Official Position (if applicable)	New
Joel	Johnson			☐
Susan	Brophy			☐
Gregg	Rothschild			☐
Jack	Krumholtz			☐
Rob	Seidman			☐
Paul	Poteet			☐
Megan	Moore		Special Advisor to the Director, Federal Housing Finance Agency; Deputy Assistant Secretary, Department of the Treasury; Special Assistant, Department of the Treasury; Legislative Assistant, House of Representatives, Office of Rep. Jesse Jackson Jr	☑

19. Interest of each foreign entity in the specific issues listed on line 16 above ☑ Check if None

Figure C.2: The Lobbying Report by Apple Inc in 2020, General Issue Codes

C.2 Additional Results on the China Shock and Lobbying

C.2.1 Additional Robustness Checks

Table C.1: Robustness. Not Averaged. Market Size and Lobbying

Dep.	$\log(1+Lobby)$		$asinh(Lobby)$		$100\times 1[Lobby>0]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline						
$China^{im}_{oc,jt}$	-0.018*	-0.018**	-0.019*	-0.019**	-0.151*	-0.153*
	(0.009)	(0.009)	(0.010)	(0.010)	(0.089)	(0.087)
$\triangle China^{oc,im}_{jt}$	0.002**	0.002**	0.002**	0.002**	0.019**	0.019**
$\times \log(Sale_{it_0})$	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)
Panel B. Export Exposure						
$China^{im}_{oc,jt}$	-0.028**	-0.028**	-0.029**	-0.030**	-0.234**	-0.240**
	(0.012)	(0.011)	(0.012)	(0.012)	(0.112)	(0.112)
$China^{im}_{oc,jt}$	0.004***	0.004***	0.004***	0.004***	0.029**	0.030**
$\times \log(Sale_{it_0})$	(0.001)	(0.001)	(0.001)	(0.001)	(.012)	(0.012)
$China^{ex}_{oc,jt}$	0.003	0.004	0.003	0.005	0.028	0.040
	(0.005)	(0.005)	(0.005)	(0.005)	(0.044)	(0.043)
$China^{ex}_{oc,jt}$	-0.001	-0.001	-0.001	-0.001	-0.007	-0.009
$\times \log(Sale_{it_0})$	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	Y	N	Y	N
State $\times$ Time FE	N	Y	N	Y	N	Y
N	33481	32667	33481	32667	33481	32667

Notes. Panel A, B and C of the table reports results from estimating Equation (3.17) using OLS. Panel D report results from estimating Equation (3.19) using OLS. The dependent variables are log one plus lobbying expenditures in columns (1) and (2), the inverse hyperbolic sine transformation of lobbying expenditures in columns (3) and (4) and a dummy variable of positive lobbying expenditures multiplied by 100 in columns (5) and (6). In Panel C, I use non trade-related lobbying expenditures as dependent variables. $China^{oc,im}_{jt}$ and $China^{oc,ex}_{jt}$ are defined in Equations (3.16) and (3.18). Robust standard errors are reported in parentheses and clustered on 3-digit SIC industries. * p<0.1; ** p<0.05; *** p<0.01.

Table C.2: Robustness. Different Proxies for Initial Size. Market Size and Lobbying

Dep.	$\log(1+Lobby)$		$asinh(Lobby)$		$100 \times 1[Lobby > 0]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Initial Level of Employment						
$China^{im}_{oc,jt}$	-0.084**	-0.100**	-0.088**	-0.105**	-0.648*	-0.771**
	(0.041)	(0.043)	(0.043)	(0.045)	(0.328)	(0.340)
$\log(Emp_{it_0})$	0.017**	0.019**	0.018**	0.020**	0.124**	0.135**
$\times \triangle China^{oc,im}_{jt}$	(0.007)	(0.008)	(0.008)	(0.009)	(0.055)	(0.061)
Panel B. Initial Level of Capital						
$China^{im}_{oc,jt}$	-0.094**	-0.112**	-0.099**	-0.118**	-0.762**	-0.909**
	(0.045)	(0.050)	(0.048)	(0.053)	(0.375)	(0.405)
$\log(Capital_{it_0})$	0.014***	0.016**	0.015***	0.017**	0.109**	0.121**
$\times \triangle China^{oc,im}_{jt}$	(0.005)	(0.006)	(0.006)	(0.006)	(0.043)	(0.049)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	Y	N	Y	N
State × Time FE	N	Y	N	Y	N	Y
N	2798	2744	2798	2744	2798	2744

Notes. Panel A and B the table reports results from estimating Equation (3.17) using OLS. The dependent variables are log one plus lobbying expenditures in columns (1) and (2), the inverse hyperbolic sine transformation of lobbying expenditures in columns (3) and (4) and a dummy variable of positive lobbying expenditures multiplied by 100 in columns (5) and (6). $China^{oc,im}_{jt}$ and $China^{oc,ex}_{jt}$ are defined in Equations (3.16) and (3.18). Capital is measured by *ppegt* from Compustat. The samples are averaged over six years. Robust standard errors are reported in parentheses and clustered on 3-digit SIC industries. * p<0.1; ** p<0.05; *** p<0.01.

Table C.3: Robustness. Trade-Related Lobbying Expenditures as the Dependent Variable. Market Size and Lobbying

Dep.	$\log(1 + Lobby)$		$asinh(Lobby)$		$100 \times 1[Lobby > 0]$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline						
$China^{im}_{oc,jt}$	0.010	0.008	0.010	0.008	0.090	0.066
	(0.025)	(0.027)	(0.025)	(0.027)	(0.220)	(0.242)
$\log(Sale_{it_0})$	0.000	0.000	0.000	0.000	0.001	0.004
$\times \triangle China^{oc,im}_{jt}$	(0.003)	(0.004)	(0.003)	(0.004)	(0.031)	(0.034)
Panel B. Export Exposure						
$China^{im}_{oc,jt}$	-0.012	-0.018	-0.012	-0.018	-0.096	-0.153
	(0.037)	(0.041)	(0.037)	(0.041)	(0.333)	(0.369)
$\log(Sale_{it_0})$	0.003	0.003	0.003	0.003	0.022	0.028
$\times \triangle China^{oc,im}_{jt}$	(0.005)	(0.006)	(0.005)	(0.006)	(0.047)	(0.051)
$China^{im}_{oc,jt}$	0.013	0.016	0.013	0.016	0.116	0.136
	(0.012)	(0.013)	(0.012)	(0.013)	(0.108)	(0.115)
$\log(Sale_{it_0})$	-0.001	-0.002	-0.001	-0.002	-0.013	-0.016
$\times \triangle China^{oc,im}_{jt}$	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)	(0.012)
Panel C. Non-Parametric Regressions						
$Q_1 China^{oc,im}_{jt}$	0.002	-0.001	0.002	-0.001	0.015	-0.014
	(0.004)	(0.006)	(0.004)	(0.006)	(0.038)	(0.060)
$Q_2 China^{oc,im}_{jt}$	-0.002	0.002	-0.002	0.002	-0.013	0.023
	(0.010)	(0.012)	(0.010)	(0.012)	(0.093)	(0.110)
$Q_3 China^{oc,im}_{jt}$	0.017	0.013	0.017	0.013	0.130	0.089
	(0.020)	(0.023)	(0.020)	(0.023)	(0.185)	(0.202)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	N	Y	N	Y	N
State $\times$ Time FE	N	Y	N	Y	N	Y
N	2798	2744	2798	2744	2798	2744

Notes. Panels A, B and C of the table reports results from estimating Equation (3.17) using OLS. Panel C reports results from estimating Equation (3.19) using OLS. The dependent variables are log one plus trade-related lobbying expenditures in columns (1) and (2), the inverse hyperbolic sine transformation of trade-related lobbying expenditures in columns (3) and (4) and a dummy variable of positive trade-related lobbying expenditures multiplied by 100 in columns (5) and (6). $China^{oc,im}_{jt}$ and $China^{oc,ex}_{jt}$ are defined in Equations (3.16) and (3.18). The samples are averaged over six years Robust standard errors are reported in parentheses and clustered on 3-digit SIC industries. * p<0.1; ** p<0.05; *** p<0.01.

C.2.2 Structural Interpretation of the China shock Regression

In this section, I show that regression model in Section 3.4.1 can be structurally derived from the model framework in Section 3.2. A firm's optimal lobbying expenditure is expressed as follows: for firm i, country c and time t,

$$1 + b^* = C^1 \pi(0; \phi, \bar{\tau}^Y, \eta)^{\frac{\theta\sigma}{1-\theta\sigma}} = C_c^1 \left(\sum_{c' \in \Omega_i^c} \left(\frac{\sigma}{\sigma - 1} \frac{w_c \tau_{cc'}}{\phi} \right)^{1-\sigma} (1 - \bar{\tau}^Y)^\sigma P_{c'}^{\sigma-1} E_{c'} \right)^{\frac{\theta\sigma}{1-\theta\sigma}},$$

where Ω_i^c is a set of firm i's markets, and C_c^1 is a constant common to all lobbying firms in country c, $\tau_{cc'}$ is an iceberg trade cost to export to country c' from country c.[1] Ω_i^c is endogenously determined in the equilibrium. Firms with higher productivity, lower exogenous distortions, or lower fixed lobbying costs will enter more foreign markets, because they can make profits even after incurring fixed export costs. $P_{c'}^{\sigma-1} E_{c'}$ measures size of market in country c'.

Taking log of both sides of the above equation, I can derive the following regression model:

$$\log(1 + b^*) = \text{Constant} + \underbrace{\frac{\theta\sigma}{1 - \theta\sigma} \left(\sum_{c' \in \Omega_i^c} \tau_{c'}^{1-\sigma} P_{c'}^{\sigma-1} E_{c'} \right)}_{\text{Market Size}} + \underbrace{\frac{\theta\sigma}{1 - \theta\sigma} ((\sigma - 1) \log \phi + \sigma \log(1 - \bar{\tau}^Y))}_{\text{Error Term}}$$

which is analogous in Equation (3.17). In the regression model in Equation (3.17), $China_{jt}^{oc,im}$ and its interaction term with a firm's size is a proxy for market size effects. Depending on firm size, a firm's optimal lobbying expenditure is differentially affected by the China shock because of market size differential. The identifying assumption is that the China shock is uncorrelated with the error term which is a function of firm productivity and exogenous distortions.

[1] If $c \neq c'$, $\tau_{cc'} = \tau_x$ and if $c = c;$, $\tau_{cc'} = 1$.

C.3 Additional Evidence on Firm Heterogeneity

This section shows that firm size alone cannot explain the lobbying pattern in the data. In Figure C.3, each dot represents a firm-year level observation with positive lobbying amounts. Within each industry and year, firms are divided into two groups based on the median of the sales distribution.

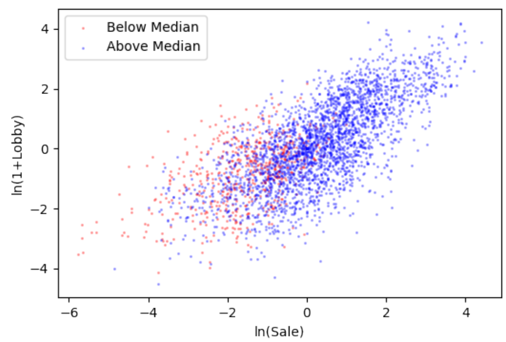


Figure C.3: Additional Fact. Firm Size and Heterogeneity

Notes. Each dot represents a firm-year observation with positive lobbying amounts. X-axis and Y-axis plot the residuals of the log of sale and lobbying on 4-digit SIC and year fixed effects respectively. I divided firms into two groups based on whether their sale is above the median or not within each industry-year.

Table C.4 reports the descriptive statistics of sales and lobbying expenditures of firms in different groups defined based on quartiles of the initial sales distribution within industry.[2] Firms with larger sizes tend to lobby more at both intensive and extensive margins. On average, 32% of the group above the third quartile participated in lobbying, whereas only 5% of the group below the first quartile participated. This shows that although firm size measured by sales and lobbying amounts are highly correlated, firm size alone cannot fully explain the pattern of lobbying. It is pretty common for small-sized firms to participate in lobbying, and their total sum of lobbying is non-negligible. The total sum of lobbying expenditures of the largest group and of the remaining groups are \$6.3 and \$1.2 billion respectively

[2]The number of firms of each group is not the same because the quartiles are defined based on the initial sales.

across the sample period. About 19% of the total lobbying expenditure comes from small or medium-sized firms. This implies an additional dimension of heterogeneity in lobbying. In my model, this additional dimension of heterogeneity is modeled as stochastic fixed lobbying costs η.

Table C.4: Additional Fact. Firm Size and Heterogeneity

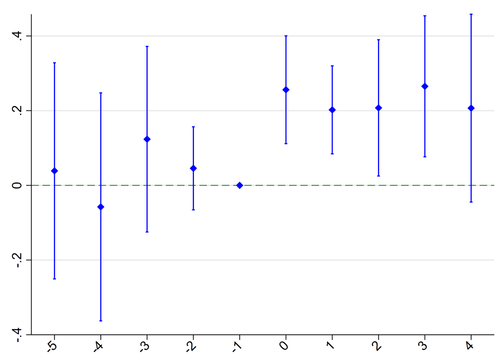
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Lobbying Expenditures ($1K)	697.2	78.67	25.13	10.70
	(2725.6)	(745.3)	(209.9)	(87.79)
$1[Lobby > 0]$	0.312	0.121	0.0817	0.0561
	(0.463)	(0.326)	(0.274)	(0.230)
Sales	6843.9	1159.9	387.1	109.7
	(21810.8)	(4814.7)	(1469.4)	(752.6)
N	9060	9940	10099	10593

Notes. This table reports the descriptive statistics of lobbying for each group. Firms are grouped by the quartiles based on their initial sales within a 4-digit SIC industry. The group with the largest and smallest size are denoted as $Q1$ and $Q4$. Standard deviation is reported in parentheses.

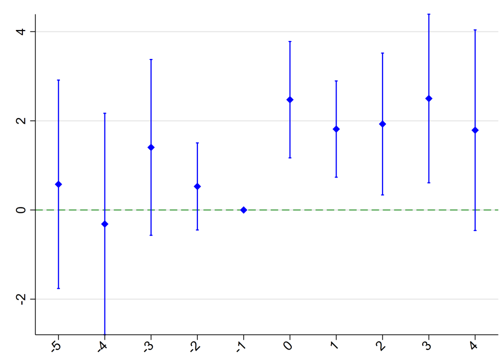
C.4 Additional Results for Estimating θ

C.4.1 Discussions on Exclusion Restrictions

Suppose the chairperson IV satisfies the relevance condition, so the IV is significantly correlated with the lobbying expenditures in the first stage. A natural concern is that the first stage results may reflect spurious correlations rather than causality. Although the exclusion restriction is fundamentally untestable, an event study can detect spurious correlations caused by reverse causality problems or preexisting confounding factors by checking pre-trends.[3] I conduct an event study to examine whether there are preexisting trends in lobbying expenditures before a local Congress member's appointment of the chairperson on the Appropriations Committees. If there were reverse causality problems or preexisting confounding factors, it would violate the parallel trend assumption. The reverse causality problem can be detected if an increase in lobbying expenditures leads to the appointment. Also, if there were preexisting confounding factors, they may show up as differential pre-trends.



Panel A. Dep. $\log(1 + \textit{Lobby})$



Panel B. Dep. $100 \times 1[\textit{Lobby} > 0]$

Figure C.4: Event Study. Lobbying and Appointment as the Chairperson of the Appropriations Committees

Notes. Panels A and B present event study coefficients β_τ in Equation (C.4.1). The dependent variable is log of one plus lobbying in Panel A and a dummy of positive lobbying in Panel B. The coefficient in $t-1$ is normalized to be zero. In both panels, firm and sector-year fixed effects are controlled. Standard errors are clustered on 3-digit SIC industries. The vertical lines show the 95% confidence intervals.

[3] For example, a reverse causality problem can arise if a firm lobbies to make a local Congress member be appointed as the chairperson.

I estimate the following event study regression:

$$y_{it} = \sum_{\tau=-4}^{4} \beta_\tau Chair_{i,\tau} + \delta_i + \delta_{jt} + \epsilon_{it},$$

where the dependent variables are log one plus lobbying or a dummy of positive lobbying multiplied 100. $Chair_{i,t-\tau}$ is the event study variables which is defined as $Chair_{i,\tau} := \mathbf{1}[t = \tau_i^{Chair} + \tau]$ where τ_i^{Chair} is the year when a local Congress member of the state in which firm i is headquartered is appointed as the chairperson and $\mathbf{1}[.]$ is the indicator function. $Chair_{i,-1}$ is normalized to be zero, so $\beta_{i,\tau}$ is interpreted as the changes of lobbying expenditures relative to the one year before the appointment. The samples include both treated and non-treated firms. Firm fixed effects δ_i and sector-time fixed effects δ_{jt} are controlled to absorb time-invariant unobservables and sectoral shocks. Standard errors are clustered on state-level, given that the chairpersonship shock is at the state-level.

Figure C.4 illustrates estimated coefficients β_τ in Equation (C.4.1). Prior to the appointment, there are no pre-trends in lobbying expenditures, but once a local Congress member becomes the chairperson, firms start increasing their lobbying expenditures. The evidence of no pre-trends in lobbying expenditures indicates that the first-stage correlation is not driven by reverse causality problems or preexisting omitted confounding factors, which bolsters the support of the identifying assumption of the instrumental variable. After the appointment, the log one plus lobbying increases by 0.1 standard deviations, and the probability of lobbying increases by 2% relative to one year before the appointment.

C.4.2 Extension to Capital Wedge

Extension: Capital Wedge. The model can incorporate firm-specific capital distortions with capital as an additional factor of production. For simplicity, I only consider closed economy, but the model presented here can be easily extended to open economy settings. Firm production function is Cobb-Douglas with labor and capital:

$$y = \phi k^{\alpha} l^{1-\alpha}.$$

There are output and capital exogenous distortions. Capital distortions decrease marginal product of capital relative to marginal product of labor. Firms can decrease output distortions and increase capital distortions through lobbying. I assume the functional form of output and capital wedges driven by exogenous distortions as follows:

$$\begin{aligned} 1 - \tau^Y &= (1 - \bar{\tau}^Y)(1 + b_Y)^{\theta_Y} \\ 1 + \tau^K &= (1 + \bar{\tau}^K)(1 + b_K)^{-\theta_K}, \end{aligned}$$

where $1 - \bar{\tau}^Y$ and $1 - \bar{\tau}^K$ are exogenous output and capital wedges. θ_Y and θ_K are the parameters that capture how lobbying effectively increases and decreases output and capital wedges respectively.

Firm maximization problem is

$$\pi = \max_{b_Y, b_K, p, l, k} (1 - \bar{\tau}^Y)(1 + b_Y)^{-\theta_Y} pq - wl - (1 + \bar{\tau}^K)(1 + b_K)^{-\theta_K} rk - f^b 1[b_Y + b_K \geq 0]$$

subject to $q = p^{-\sigma} P^{\sigma-1} E$ where q is the demand that firm faces. Solving the model, I can derive two following regression models

$$\log MRPL_{i,t+1} = \log \frac{\text{Sale}_{it}}{L_{it}} = -\theta_Y \log(1 + b_Y^*) + \epsilon_{it}$$

and

$$\log \frac{MRPK_{i,t+1}}{MRPL_{i,t+1}} = \log \frac{L_{it}}{K_{it}} = -\theta_K \log(1 + b_K^*) + \epsilon_{it},$$

where b_Y^* and b_K^* are optimal lobbying expenditures spent for output wedges and capital wedges.

In the data, I observe the total expenditure $b_Y^* + b_K^*$, but not b_Y^* and b_K^* separately. However, with the Cobb-Douglass production function, b_Y^* and b_K^* are proportional to the total lobbying expenditure plus some constant term, that is, $1+b_Y^* = C_Y(2+b_Y^*+b_K^*)$ and $1+b_K^* = C_K(2+b_Y^*+b_K^*)$, where $C_Y = \theta_Y\sigma/(\theta_Y\sigma - \theta_K\alpha)$ and $C_K = -\theta_K\alpha/(\theta_Y\sigma - \theta_K\alpha)$. Therefore, with the Cobb-Douglas constant return to scale production function, I can still recover θ_Y and θ_K using the total expenditure of lobbying observed in the data.

I estimate the following regressions in long differences using the chairperson IV:

$$\log(\text{Sale/Emp})_{i,t+1} = \theta_Y \log(2+b_{it}^*) + \mathbf{X}_{it}'\boldsymbol{\beta} + \delta_i^Y + \delta_{jt}^Y + \log(1-\bar{\tau}_{it}^Y)$$

$$\log(\text{Emp/Capital})_{i,t+1} = \theta_K \log(2+b_{it}^*) + \mathbf{X}_{it}'\boldsymbol{\beta} + \delta_i^K + \delta_{jt}^K + \log(1-\bar{\tau}_{it}^K),$$

where δ are fixed effects. I control the same set of fixed effects and firm-level controls with the baseline regression model. I also control 4-digit industry-specific fixed effects and firm fixed effects. The estimated θ_K are reported in columns (1)-(3) of Table C.5. Across different specifications, the estimated coefficients are statistically insignificant. In columns (4)-(6), I use log(Value-Added/K) as an alternative dependent variable, but the estimated coefficients are also statistically insignificant.

Table C.5: Robustness. MRPK. Recovering θ_K

Dep.	$\log(wL/K)$			$\log(Sale/K)$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+b^*_{it})$	-0.011	0.016	0.020	-0.008	-0.060	-0.063
	(0.007)	(0.027)	(0.034)	(0.007)	(0.038)	(0.047)
KP-F	.	31.81	26.90	.	31.81	26.90
Industry $\times$ Time FE	Y	Y	Y	Y	Y	Y
Firm Control	N	N	Y	N	N	Y
N	1216	1216	1216	1216	1216	1216

Notes. This table reports OLS and IV estimates of Equation (3.13). The dependent variable is a labor-capital ratio in columns (1)-(3), and the dependent variable is a log of MRPK in columns (4)-(6). The OLS estimates are reported in columns (1) and (4). The IV estimates are reported in columns (2), (3), (5), and (6). The IV is a dummy variable which equals one if a Congress member of the state where a firm is headquartered becomes a chair of the Appropriations Committees in the House or Senate. Firm control includes dummies indicating quantiles of a firm's initial sales. KP-F is Kleibergen-Paap F-statistics. The samples are averaged over six years. Standard errors are clustered at the state level. * p<0.1; ** p<0.05; *** p<0.01.

C.4.3 Additional Robustness Checks

ETR is an imperfect proxy for firm-specific tax rates, so the transformation into $\log(1 - ETR)$ may magnify measurement errors. To show that this is not the issue, I conduct the same analysis with a log of ETR as an alternative dependent variable. The results are reported in columns (1)-(3) of Table C.6. Instead of setting ETR to 0.5 at a maximum, I reset 1 at a maximum and run the analysis to examine whether different winsorization schemes drive the results. The estimated coefficients reported in columns (4)-(6) of Table C.6 show that the results are robust to different functional forms of dependent variables and winsorization schemes.

Table C.6: Recovering θ. Robustness. Different ETR Measures.

Dep.	$\log(ETR)$			$\log(ETR1)$		
	OLS	IV		OLS	IV	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1 + b^*_{it})$	0.017	-0.193**	-0.238**	0.019	-0.191**	-0.237**
	(0.016)	(0.090)	(0.098)	(0.016)	(0.091)	(0.098)
KP-F	.	23.25	18.96	.	23.25	18.96
Industry FE	Y	Y	Y	Y	Y	Y
State Control	Y	Y	Y	Y	Y	Y
Firm Control	N	N	Y	N	N	Y
N	873	873	873	873	873	873

Notes. This table reports OLS and IV estimates of Equation (3.13). The dependent variable is log of ETR in columns (1)-(3) and the dependent variable is log of ETR that was winsorized at 1 instead of 0.5. ETR is defined in Equation (3.14). The OLS estimates are reported in columns (1) and (4). The IV estimates are reported in columns (2), (3), (5) and (6). The IV is a dummy variable which is equal to one if a Congress member of the state where a firm is headquartered in becomes a chair of the Appropriations Committee in the House or Senate. Firm control includes dummies indicating quantiles of a firm's initial sales. The samples are averaged over six years. Standard errors are clustered at the state-level. * p<0.1; ** p<0.05; *** p<0.01.

C.4.4 Additional Tables and Figures

Table C.7: First Stage Results

Second Stage Dep.	$\log(1/MRPL)$		$\log(1-ETR)$	
	(1)	(2)	(3)	(4)
Chairperson IV	0.942***	0.836***	0.942***	0.836***
	(0.167)	(0.161)	(0.167)	(0.161)
Industry FE	Y	Y	Y	Y
State Control	Y	Y	Y	Y
Firm Control	N	Y	N	Y
N	1216	1216	1216	1216

Notes. This table reports the first stage results of the IV estimates of Equation (3.13). The dependent variable is log one plus lobbying. Firm control includes dummies indicating quantiles of a firm's initial sales. Standard errors are clustered at the state-level. * p<0.1; ** p<0.05; *** p<0.01.

C.5 Quantitative Appendix

C.5.1 Calibration Procedure

This section describes the calibration procedure using the method of moments. Parameters Θ minimize the following constrained maximization problem

$$\hat{\Theta} = argmin_{\Theta}\{(\mathbf{m} - \mathbf{m}(\Theta))'\mathbf{W}(\mathbf{m} - \mathbf{m}(\Theta)) \quad \text{subject to } L(\Theta) = 0$$

where $\mathbf{m}$ and $\mathbf{m}(\Theta)$ are empirical and model moments, W is the weighting matrix, and $L(\Theta)$ is the constraint imposed by the equilibrium conditions.

The constraints $L(\Theta) = 0$ are as follows:

$$\begin{aligned}
\text{(Balanced trade)} \quad & \int_{\omega \in \Omega_H^x} p^x(\omega) q^x(\omega) d\omega = \int_{\omega \in \Omega_F^x} p^x(\omega) q^x(\omega) d\omega \\
\text{(Labor market clearing of Home)} \quad & \int_{\omega \in \Omega_H} l(\omega) d\omega = L_H \\
\text{(Labor market clearing of Foreign)} \quad & \int_{\omega \in \Omega_F} l(\omega) d\omega = L_F \\
\text{(Goods market clearing of Home)} \quad & E_H = w_H L_H + \Pi_H + T_H \\
\text{(Goods market clearing of Foreign)} \quad & E_F = w_F L_F + \Pi_F + T_F
\end{aligned}$$

I set W to be the identity matrix. The moments are normalized to convert the difference between the model and the empirical moments into the percentage deviation. The solution to the problem is not guaranteed to be the global minimum. Therefore, I solve the constrained minimization problem multiple times with different starting points to deal with the local minimum problem.

C.6 Mathematical Derivation

C.6.1 Derivation of optimal lobbying amounts and profits.

I derive expressions for a firm's optimal lobbying amounts and profits conditional on lobbying. I first characterize non-exporters' optimal lobbying amounts and profits. Conditional on spending lobbying amounts of b, a firm's output wedge is given by $(1-\bar{\tau}^Y)(1+b)^\theta$. Under monopolistic competition with CES demand, a firm charges constant mark up over marginal costs. A firm's profit is

$$\pi^d(b;\phi,\bar{\tau}^Y,\eta) = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_c}{\phi}\right)^{1-\sigma}((1-\bar{\tau}^Y)(1+b)^\theta)^\sigma P_c^{\sigma-1}E_c - P_c b - P_c f^b$$
$$= \tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)(1+b)^{\theta\sigma} - P_c b - P_c f^b$$

where $\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)$ is variable profits conditional on not lobbying for non-exporters. A firm chooses the optimal lobbying amounts that maximizes profits in the above equation, which is characterized by the first-order condition (FOC). Taking the derivative with respect to b,

$$P_c = \theta\sigma\tilde{\pi}(0;\phi,\bar{\tau}^Y,\eta)(1+b)^{(\theta\sigma-1)}$$

Form the above equation, I can obtain that

$$b^{d*} = \left(\frac{\theta\sigma}{P_c}\right)^{\frac{1}{1-\theta\sigma}}\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)^{\frac{1}{1-\theta\sigma}} - 1$$

After substituting the optimal lobbying amounts, I obtain that

$$\pi^d(b^{d*};\phi,\bar{\tau}^Y,\eta) = C_c^2\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)^{\frac{1}{1-\theta\sigma}} - w_c f_c - P_c[f^b\eta - 1].$$

Now consider an exporter. An exporter's profit is

$$\pi^x(b;\phi,\bar{\tau}^Y,\eta) = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_c}{\phi}\right)^{1-\sigma}$$
$$\times\left(P_c^{\sigma-1}E_c + \tau_x P_{c'}^{\sigma-1}E_{c'}\right)\times((1-\bar{\tau}^Y)(1+b)^{\theta})^{\sigma}$$
$$-P_c b - P_c f^b\eta - w_c f_c^x$$
$$= \tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)(1+b)^{\theta\sigma} - P_c b - P_c f^b\eta - w_c f_c^x,$$

where $\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta)$ is variable profits conditional on lobbying for exporters. Taking the first-order condition with respect to b, I obtain that

$$b^{x*} = \left(\frac{\theta\sigma}{P_c}\right)^{\frac{1}{1-\theta\sigma}}(\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)+\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta))^{\frac{1}{1-\theta\sigma}} - 1.$$

After substitution the optimal lobbying amounts to the above equation, an exporter's profit is derived as follows:

$$\pi^x(b^{x*};\phi,\bar{\tau}^Y,\eta) = C_c^2(\tilde{\pi}^d(0;\phi,\bar{\tau}^Y,\eta)+\tilde{\pi}^x(0;\phi,\bar{\tau}^Y,\eta))^{\frac{1}{1-\theta\sigma}} - w_c f_c - P_c[f^b\eta - 1].$$

C.6.2 Proof of Proposition III.3

Using that lobbying is increasing in variable profits and variable profits increase in ϕ, $1-\bar{\tau}^Y$, and $P_c^{\sigma-1}E_c + x(P_{c'}^*)^{\sigma-1}E_{c'}$, Proposition III.3(i) can be proven.

For given $(1-\bar{\tau}^Y, \eta)$, because $1-\theta\sigma < 1$ under Assumption III.1, the RHS of Equation 3.7 increases in ϕ by larger magnitude than the LHS of Equation (3.7). This implies that for a given level of fixed lobbying costs $f^b\eta$, a firm with $\phi > \bar{\phi}_c^b(\bar{\tau}^Y, \eta)$ participate in lobbying. Because a firm with lower $\bar{\tau}^Y$ has a larger tax gain post-lobbying and a firm with higher η has a larger fixed lobbying cost, $\bar{\phi}_c^b(\bar{\tau}^Y, \eta)$ increases in both $\bar{\tau}^Y$ and η. □

C.6.3 Proof of Proposition III.5

Because the results of Proposition III.5 are derived under the closed economy assumption, I omit subscripts indexing countries. I first provide two useful expressions for the proofs of Proposition III.5.

Useful Expression 1. Suppose Y_1 and Y_2 follow a joint normal distribution. Define $X_i = exp^{Y_i}$ for $i = 1, 2$. By definition, X_1 and X_2 follow a joint log-normal distribution. Then, using that

$$\int\int X_1 X_2 dF_{X_1} dF_{X_2} = \int\int exp^{Y_1+Y_2} dF_{Y_1} dF_{Y_2} = \mathbb{E}[exp^{Y_1+Y_2}]$$

and that $Y_1 + Y_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2 + 2\rho\sigma_1\sigma_2)$, I can obtain

$$e^{Y_1+Y_2} \sim \log N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2 + 2\rho\sigma_1\sigma_2).$$

From the above equations, I can derive the following first useful expression.

$$\mathbb{E}[X_1 X_2] = \mathbb{E}[exp^{Y_1+Y_2}] = exp(\mu_1 + \mu_2 + \frac{1}{2}[\sigma_1^2 + \sigma_2^2 + 2\rho\sigma_1\sigma_2]).$$

This gives the analytical expression for the expectation of multiplication of two log-normally distributed random variables.

Useful Expression 2. TFP of the aggregate economy is defined as output per worker $TFP = Q/L$, where Q is the aggregate output and L is the labor. TFP can be rewritten as follows:

$$\frac{1}{TFP} = \frac{L}{Q} = \frac{\int l(\omega)d\omega}{Q} = \int \frac{y(\omega)}{Q}\frac{1}{\phi(\omega)}d\omega = \int \frac{1}{\phi(\omega)}\left(\frac{p(\omega)}{P}\right)^{-\sigma} d\omega.$$

Firm's optimal pricing is

$$p = \frac{\sigma}{\sigma-1}\frac{w}{\phi}\left((1-\bar{\tau}^Y)(1+b^*)^\theta\right)^{-1},$$

where b^* is a firm's optimal lobbying amounts. I obtain the second useful expression:

$$TFP = M^{\frac{1}{\sigma-1}}\frac{[\int \phi^{\sigma-1}((1-\bar{\tau}^Y)(1+b^*)^\theta)^{\sigma-1}dF(\phi, 1-\bar{\tau}^Y)]^{-\frac{\sigma}{1-\sigma}}}{\int \phi^{\sigma-1}((1-\bar{\tau}^Y)(1+b^*)^\theta)^{\sigma}dF(\phi, 1-\bar{\tau}^Y)}.$$

Proof of Proposition III.5(i) (The Efficient Economy). If there are no exogenous distortions and lobbying is not allowed, using Equation (C.6.3), the TFP of the efficient economy reduces to

$$TFP_{eff} = M^{\frac{1}{\sigma-1}}[\int \phi^{\sigma-1}dF(\phi)]^{\frac{1}{\sigma-1}}.$$

Taking log of both sides of the above equation, I obtain that

$$\log(TFP_{eff}) = \frac{1}{\sigma-1}\log M + \mathbb{E}[\log\phi] + \frac{(\sigma-1)}{2}Var(\log\phi),$$

where $\frac{1}{\sigma-1}\log M = 0$ under Assumption III.4(iv). This proves Proposition III.3(i). $\square$

Proof of Proposition III.5(ii) (The Exogenous Wedge Economy). If there were only exogenous distortions, the TFP of the exogenous wedge economy reduces to

$$TFP_{exo} = M^{\frac{1}{\sigma-1}}\frac{[\int \phi^{\sigma-1}(1-\bar{\tau}^Y)^{\sigma-1}dF(\phi, 1-\bar{\tau}^Y)]^{-\frac{\sigma}{1-\sigma}}}{\int \phi^{\sigma-1}(1-\bar{\tau}^Y)^{\sigma}dF(\phi, 1-\bar{\tau}^Y)}.$$

The log of the numerator is expressed as

$$\begin{aligned}
&\log[\int \phi^{\sigma-1}(1-\bar{\tau}^Y)^{(\sigma-1)}dF(\phi,1-\bar{\tau}^Y)]^{-\frac{\sigma}{1-\sigma}}\\
&=\frac{\sigma}{\sigma-1}\Bigg[(\sigma-1)\mathbb{E}[\log\phi]+(1-\sigma)\\
&\times\mathbb{E}[\log(1-\bar{\tau}^Y)]+\frac{(\sigma-1)^2}{2}Var(\log\phi)\\
&+\frac{(\sigma-1)^2}{2}Var(\log(1-\bar{\tau}^Y))\\
&+\sigma(\sigma-1)^2Cov(\log\phi,\log(1-\bar{\tau}^Y))\Bigg]\\
&=\sigma\mathbb{E}[\log\phi]-\sigma\mathbb{E}[\log(1-\bar{\tau}^Y)]+\frac{\sigma(\sigma-1)}{2}Var(\log\phi)\\
&-\frac{(\sigma-1)\sigma}{2}Var(\log(1-\bar{\tau}^Y))+(\sigma-1)\sigma Cov(\log\phi,\log(1-\bar{\tau}^Y)).
\end{aligned}$$

The log of the denominator is expressed as

$$\begin{aligned}
&\log\int\phi^{\sigma-1}(1-\bar{\tau}^Y)^{\sigma}dF(\phi,1-\bar{\tau}^Y)\\
&\qquad=(\sigma-1)\mathbb{E}[log\phi]-\sigma\mathbb{E}[\log(1-\bar{\tau}^Y)+\frac{(\sigma-1)^2}{2}Var(\log\phi)\\
&\qquad\qquad+\frac{\sigma^2}{2}Var(\log(1-\bar{\tau}^Y))-(\sigma-1)\sigma Cov(\log\phi,\log(1-\bar{\tau}^Y)).
\end{aligned}$$

Subtracting the log of the denominator from the log of the numerator,

$$\log(TFP_{exo})=\frac{1}{\sigma-1}\log M+\mathbb{E}[\log\phi]+\frac{(\sigma-1)}{2}Var(\log\phi)-\frac{\sigma}{2}Var(\log(1-\bar{\tau}^Y)),$$

where $\frac{1}{\sigma-1}\log M=0$ under Assumption III.4(iv). This proves Proposition III.5(ii).

□

Proof of Proposition III.5(iii) (The Lobbying Economy). Using the second formula, the TFP of the lobbying economy reduces to

$$TFP_{endo}=M^{\frac{1}{\sigma-1}}\frac{[\int\phi^{\sigma-1}(1-\bar{\tau}^Y)(1+b^*)^{\theta})^{\sigma-1}dF(\phi,1-\bar{\tau}^Y)]^{-\frac{\sigma}{1-\sigma}}}{\int\phi^{\sigma-1}((1-\bar{\tau}^Y)(1+b^*)^{\theta})^{\sigma}dF(\phi,1-\bar{\tau}^Y)}.$$

The optimal lobbying expenditure in a closed economy is expressed as

$$1+b^*=\left(\frac{\theta\sigma}{P}\right)^{\frac{1}{1-\theta\sigma}}\left[\frac{1}{\sigma}\left(\mu\frac{w}{\phi}\right)^{1-\sigma}(1-\bar{\tau}^Y)^{\sigma}P^{\sigma-1}E\right]^{\frac{1}{1-\theta\sigma}}.$$

Define

$$\bar{C} = \left[\frac{\sigma\theta}{P}\frac{1}{\sigma}(\mu w)^{1-\sigma}P^{\sigma-1}E\right]^{\frac{1}{1-\theta\sigma}}.$$

The log of the numerator can be expressed as

$$\begin{aligned}
&\log\left[\int \phi^{\sigma-1}((1-\bar{\tau}^Y)(1+b^*)^\theta)^{\sigma-1}dF(\phi,1-\bar{\tau}^Y)\right]^{-\frac{\sigma}{1-\sigma}} \\
&= \frac{\sigma}{\sigma-1}\left[(\theta(\sigma-1)\log\bar{C} + \log\int \phi^{\frac{(\sigma-1)(1-\theta)}{1-\theta\sigma}}(1-\bar{\tau}^Y)^{\frac{\sigma-1}{1-\theta\sigma}}\right] \\
&= \theta\sigma\log\bar{C} + \frac{\sigma(1-\theta)}{(1-\theta\sigma)}\mathbb{E}[\log\phi] + \frac{\sigma}{1-\theta\sigma}\mathbb{E}[\log(1-\bar{\tau}^Y)] \\
&+ \frac{1}{2}\frac{(\sigma-1)\sigma(1-\theta)^2}{(1-\theta\sigma)^2}Var(\log\phi) + \frac{1}{2}\frac{(\sigma-1)\sigma}{(1-\theta\sigma)^2}Var(\log(1-\bar{\tau}^Y)) \\
&+ \frac{\sigma(1-\sigma)(1-\theta)}{(1-\theta\sigma)^2}Cov(\log\phi,\log(1-\bar{\tau}^Y)),
\end{aligned}$$

and the log of the denominator can be expressed as

$$\begin{aligned}
&\log\left[\int \phi^{\sigma-1}((1-\bar{\tau}^Y)(1+b^*)^\theta)^{\sigma}dF(\phi,1-\bar{\tau}^Y)\right] \\
&= \sigma\theta\log\bar{C} + \log\left[\int \phi^{\frac{\sigma-1}{1-\theta\sigma}}(1-\bar{\tau}^Y)^{\frac{\sigma}{1-\theta\sigma}}dF(\phi,1-\bar{\tau}^Y)\right] \\
&= \sigma\theta\log\bar{C} + \frac{\sigma-1}{1-\theta\sigma}\mathbb{E}[\log\phi] + \frac{\sigma}{1-\theta\sigma}\mathbb{E}[\log(1-\bar{\tau}^Y)] \\
&\qquad + \frac{1}{2}\frac{(\sigma-1)^2}{(1-\theta\sigma)^2}Var(\log\phi) + \frac{1}{2}\frac{\sigma^2}{(1-\theta\sigma)^2}Var(\log(1-\bar{\tau}^Y)) \\
&+ \frac{(\sigma-1)\sigma}{(1-\theta\sigma)^2}Cov(\log\phi,\log(1-\bar{\tau}^Y))
\end{aligned}$$

Subtracting the log of the denominator from the log of the numerator,

$$\begin{aligned}
&\log TFP_{endo} = \frac{1}{\sigma-1}\log M \\
&+ \mathbb{E}[\log\phi] + \frac{(\sigma-1)}{2}\left(\frac{(\sigma[(1-\theta)^2-1]+1)}{(1-\theta\sigma)^2}\right)Var(\log\phi) \\
&- \frac{\sigma\theta^2}{2}\frac{1}{(1-\theta\sigma)^2}Var(\log(1-\bar{\tau}^Y)) - \frac{(\sigma-1)\sigma\theta}{(1-\theta\sigma)^2}Cov(\log\phi,\log(1-\bar{\tau}^Y)),
\end{aligned}$$

where $\frac{1}{\sigma-1}\log M = 0$ under Assumption III.4(iv).

Under Assumption III.1(i), both $\frac{1}{(1-\theta\sigma)^2} > 1$ and $\frac{(\sigma-1)\sigma\theta}{(1-\theta\sigma)^2} > 0$ hold. It remains to show that $\left(\frac{(\sigma[(1-\theta)^2-1]+1)}{(1-\theta\sigma)^2}\right) < 1$. Note that

$$\left(\frac{(\sigma[(1-\theta)^2-1]+1)}{(1-\theta\sigma)^2}\right) < 1 \Leftrightarrow \sigma[(1-\theta)^2-1]+1 < (1-\theta\sigma)^2$$

$$\Leftrightarrow \sigma[\theta^2-2\theta] < \theta^2\sigma^2 - 2\theta\sigma$$

$$\Leftrightarrow 1 < \sigma,$$

where the last inequality holds under Assumption III.1. □

C.6.4 Proof of Proposition III.6

Proof of Proposition III.6(i). This comes from the expressions of the TFPs of the efficient, exogenous wedge, and lobbying economies. □

Proof of Proposition III.6(ii). $\log TFP_{eff} \geq \log TFP_{exo}$ is trivial. It remains to show that $\log TFP_{eff} \geq \log TFP_{endo}$. Taking the difference between $\log TFP_{eff}$ and

$\log TFP_{endo}$, I can obtain that

$$
\begin{aligned}
&\log TFP_{eff} - \log TFP_{endo} \\
&= \left(\frac{\sigma-1}{2}\right)\left[1 - \frac{1+\sigma[(1-\theta)^2-1]}{(1-\theta\sigma)^2}\right] Var(\log\phi) \\
&+ \frac{\sigma}{2}\frac{1}{(1-\theta\sigma)^2} Var(\log(1-\bar{\tau}^Y)) \\
&+ \frac{(\sigma-1)\sigma\theta}{(1-\theta\sigma)^2} \times \underbrace{Cov(\log\phi, \log(1-\bar{\tau}^Y))}_{=Corr(\log\phi,\log(1-\bar{\tau}^Y))} \\
&\times \sqrt{Var(\log\phi)}\sqrt{Var(\log(1-\bar{\tau}^Y))} \\
&= \frac{\sigma}{2(1-\theta\sigma)^2}\Big[\theta^2(\sigma-1)^2 Var(\log\phi) \\
&+ 2(\sigma-1)\theta Corr(\log\phi, \log(1-\bar{\tau}^Y))\sqrt{Var(\log\phi)}\sqrt{Var(\log(1-\bar{\tau}^Y))} \\
&+ Var(\log(1-\bar{\tau}^Y))\Big] \\
&\geq \frac{\sigma}{2(1-\theta\sigma)^2} \\
&\times \Big[\theta^2(\sigma-1)^2 Var(\log\phi) - 2(\sigma-1)\theta\sqrt{Var(\log\phi)} \\
&\sqrt{Var(\log(1-\bar{\tau}^Y))} + Var(\log(1-\bar{\tau}^Y))\Big] \\
&= \frac{\sigma}{2(1-\theta\sigma)^2}\left(\theta(\sigma-1)\sqrt{Var(\log\phi)} - \sqrt{Var(\log(1-\bar{\tau}^Y))}\right)^2 \geq 0,
\end{aligned}
$$

where the last inequality comes from that correlation between two random variables are bounded below by -1. □

Proof of Proposition III.6(iii). Note that

$$
\begin{aligned}
&\log TFP_{endo} \geq \log TFP_{exo} \\
&\qquad \Leftrightarrow -2(\sigma-1)Cov(\log\phi, \log(1-\bar{\tau}^Y)) \geq \theta(\sigma-1)^2 Var(\log\phi) \\
&\qquad\qquad + \sigma(2-\theta\sigma)Var(\log(1-\bar{\tau}^Y)).
\end{aligned}
$$

Because the RHS of the above equation is always non-negative, the above inequality holds only if $Cov(\log\phi, \log(1-\bar{\tau}^Y)) \leq 0$. □

C.6.5 Proof of Proposition III.7

Proof of Proposition III.7(i). Because the results of Proposition III.7(i) are derived under the closed economy assumption, I omit the subscripts indexing countries. Under Assumptions III.1 and III.4, every firm is lobbying. Note that the optimal lobbying expenditure in a closed economy is

$$1+b^{*}=C^{1}\left[\frac{1}{\sigma}\left(\mu\frac{w}{\phi}\right)^{1-\sigma}(1-\bar{\tau}^{Y})^{\sigma}P^{\sigma-1}E\right]^{\frac{1}{1-\theta\sigma}},\qquad C^{1}=(\theta\sigma/P)^{1/(1-\theta\sigma))}.$$

Also, note that $Cov(\log(1+b^{*}),\log(1-\bar{\tau}^{Y}))$ can be written as

$$\begin{aligned}&Cov(\log(1+b^{*}),\log(1-\bar{\tau}^{Y}))\\&\qquad=\mathbb{E}[\log(1+b^{*})\log(1-\bar{\tau}^{Y})]-\mathbb{E}[\log(1+b^{*})]\times\mathbb{E}[\log(1-\bar{\tau}^{Y})].\end{aligned}$$

Substituting the equation of the optimal lobbying expenditures into $\mathbb{E}[\log(1+b^{*})\log(1-\bar{\tau}^{Y})]$, $\mathbb{E}[\log(1+b^{*})\log(1-\bar{\tau}^{Y})]$ can be expressed as

$$\begin{aligned}\mathbb{E}[\log(1+b^{*})\log(1-\bar{\tau}^{Y})]&=\frac{\sigma-1}{1-\theta\sigma}\mathbb{E}[\log\phi\log(1-\bar{\tau}^{Y}))]\\&\quad+\frac{\sigma}{1-\theta\sigma}\mathbb{E}[(\log(1-\bar{\tau}^{Y})^{2}]\\&\quad+\frac{1}{1-\theta\sigma}\mathbb{E}[\log(1-\bar{\tau}^{Y})]\times\left[C^{1}+\log\left(\frac{1}{\sigma}(\mu w)^{1-\sigma}\right)\right.\\&\qquad\left.+\log(P^{\sigma-1}E)\right].\end{aligned}$$

Then, $\mathbb{E}[\log(1+b^{*})]\times\mathbb{E}[\log(1-\bar{\tau}^{Y})]$ can be written as

$$\begin{aligned}\mathbb{E}[\log(1+b^{*})]\times\mathbb{E}[\log(1-\bar{\tau}^{Y})]&=\frac{\sigma-1}{1-\theta\sigma}\mathbb{E}[\log\phi]\\&\quad\times\mathbb{E}[\log(1-\bar{\tau}^{Y})]+\frac{\sigma}{1-\theta\sigma}(\mathbb{E}[\log(1-\bar{\tau}^{Y})])^{2}\\&\quad+\frac{1}{1-\theta\sigma}\mathbb{E}[\log(1-\bar{\tau}^{Y})]\\&\qquad\times\left[C^{1}+log\left(\frac{1}{\sigma}(\mu w)^{1-\sigma}\right)+\log P^{\sigma-1}E\right].\end{aligned}$$

Using the above equations, I can obtain that

$$
\begin{aligned}
Cov(\log(1+b^*)\log(1-\bar{\tau}^Y)) &= \mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)] \\
&\quad - \mathbb{E}[\log(1+b^*)] \times \mathbb{E}[\log(1-\bar{\tau}^Y)] \\
&= \frac{\sigma-1}{1-\theta\sigma}\Big(\mathbb{E}[\log\phi\log(1-\bar{\tau}^Y)] - \mathbb{E}[\log\phi] \times \mathbb{E}[\log(1-\bar{\tau}^Y)]\Big) \\
&\quad + \frac{\sigma}{1-\theta\sigma}\Big(\mathbb{E}[(\log(1-\bar{\tau}^Y))^2] - \mathbb{E}[\log(1-\bar{\tau}^Y)]^2\Big),
\end{aligned}
$$

which is equivalent to $Cov(\log\phi, \log(1-\bar{\tau}^Y)) + \frac{\sigma}{1-\theta\sigma}Var(\log(1-\bar{\tau}^Y))$. □

Proof of Proposition III.7(ii). Note that

$$
\begin{aligned}
Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)|b^*>0) &= \mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^*>0] \\
&\quad - \mathbb{E}[\log(1+b^*)|b^*>0] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^*>0].
\end{aligned}
$$

$\mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^*>0]$ can be written as

$$
\begin{aligned}
\mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^*>0] = \sum_{x'\in\{0,1\}} \Big\{&\mathbb{P}[b^*\geq 0, x^*=x'] \\
&\times \mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^*\geq 0, x^*=x']\Big\}
\end{aligned}
$$

where x^* is a firm's optimal export decision. Similarly, $\mathbb{E}[\log(1+b^*)|b^*>0]\times\mathbb{E}[\log(1-\bar{\tau}^Y)|b^*>0]$ can be written as

$$
\begin{aligned}
&\mathbb{E}[\log(1+b^*)|b^*>0] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^*>0] \\
&\qquad = \sum_{x'\in\{0,1\}} \Big\{\mathbb{P}[b^*\geq 0, x^*=x'] \\
&\qquad\qquad \times \mathbb{E}[\log(1+b^*)|b^*\geq 0, x^*=x']\Big\}.
\end{aligned}
$$

Using the above expressions, $Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)|b^*>0)$ can be expressed as

$$Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)|b^*>0) = \sum_{x'\in\{0,1\}} \mathbb{P}[b^* \geq 0, x^* = x'] \Big(\mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] - \mathbb{E}[\log(1+b^*)|b^* \geq 0, x^* = x'] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] \Big).$$

Also, the optimal lobbying expenditure is

$$1+b^* = C_c^1 \left[\frac{1}{\sigma} \left(\mu \frac{w_c}{\phi} \right) (1-\bar{\tau}^Y)^\sigma (P_c^{\sigma-1} E_c + x^* \tau_x^{1-\sigma} P_{c'}^{\sigma-1} E_{c'}) \right]^{\frac{1}{1-\theta\sigma}},$$

where $C_c^1 = (\theta\sigma/P_c)^{1/(1-\theta\sigma))}$.

Using the above equation, $\mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^* \geq 0, x = x']$ is computed as

$$\begin{aligned}
&\mathbb{E}[\log(1+b^*)\log(1-\bar{\tau}^Y)|b^* \geq 0, x = x'] \\
&= \frac{\sigma-1}{1-\theta\sigma} \mathbb{E}[\log\phi \log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] \\
&+ \frac{\sigma}{1-\theta\sigma} \mathbb{E}[(\log(1-\bar{\tau}^Y))^2|b^* \geq 0, x^* = x'] \\
&+ \frac{1}{1-\theta\sigma} \log\left(C_c^1 \frac{1}{\sigma} (\mu w_c)^{1-\sigma} (P_c^{\sigma-1} E_c + x' \tau_x^{1-\sigma} P_{c'}^{\sigma-1} E_{c'}) \right) \\
&\times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'].
\end{aligned}$$

Similarly, $\mathbb{E}[\log(1+b^*)|b^* \geq 0, x^* = x']\mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x']$ is computed as

$$\begin{aligned}
&\mathbb{E}[\log(1+b^*)|b^* \geq 0, x^* = x'] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] \\
&= \frac{\sigma-1}{1-\theta\sigma} \mathbb{E}[\log\phi|b^* \geq 0, x^* = x'] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] \\
&+ \frac{\sigma}{1-\theta\sigma} (\mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'])^2 \\
&+ \frac{1}{1-\theta\sigma} \log\left(C_c^1 \frac{1}{\sigma} (\mu w_c)^{1-\sigma} (P_c^{\sigma-1} E_c + x' \tau_x^{1-\sigma} P_{c'}^{\sigma-1} E_{c'}) \right) \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x']
\end{aligned}$$

Using the above equations, I can obtain

$$
\begin{aligned}
Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)|b^*>0) = &\sum_{x'\in\{0,1\}} \mathbb{P}[b^* \geq 0, x^* = x'] \\
&\times \Bigg[(\mathbb{E}[\log\phi \log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x'] \\
&- \mathbb{E}[\log\phi|b^* \geq 0, x = x'] \times \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x']) \\
&+ (\mathbb{E}[(\log(1-\bar{\tau}^Y))^2|b^* \geq 0, x = x'] \\
&- \mathbb{E}[\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x']^2)\Bigg],
\end{aligned}
$$

which is equivalent to

$$
\begin{aligned}
Cov(\log(1+b^*), \log(1-\bar{\tau}^Y)|b^*>0) = &\sum_{x'\in\{0,1\}} \mathbb{P}[b^* \geq 0, x^* = x'] \\
&\times \Bigg(\frac{\sigma-1}{1-\theta\sigma} \times Cov(\log\phi, \log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x']) \\
&+ \frac{\sigma}{1-\theta\sigma} Var(\log(1-\bar{\tau}^Y)|b^* \geq 0, x^* = x')\Bigg).
\end{aligned}
$$

The events $\{b^* \geq 0, x^* = 1\}$ and $\{b^* \geq 0, x^* = 0\}$ are equivalent to $\{\phi \geq \bar{\phi}_c^b(\bar{\tau}^Y, \eta), \phi \geq \bar{\phi}_c^x(\bar{\tau}^Y, \eta)\}$ and $\{\phi \geq \bar{\phi}_c^b(\bar{\tau}^Y, \eta), \phi \leq \bar{\phi}_c^x(\bar{\tau}^Y, \eta)\}$, where $\bar{\phi}_c^b(\bar{\tau}^Y, \eta)$ and $\bar{\phi}_c^x(\bar{\tau}^Y, \eta)$ are the lobbying and export cutoffs defined in Equations (3.7) and (3.8), which proves Proposition 4(ii).

$\square$

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