# Technology Adoption and Late Industrialization*


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**JOB MARKET PAPER**

November, 2021

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**Abstract**

We study how the adoption of foreign technology and the 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 productivity 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 micro data and econometric estimates. We evaluate the effects of the Korean government policy that temporarily provided adoption subsidies to heavy manufacturing firms in the 1970s. Had no adoption subsidies been provided, Korea would have converged to a less industrialized steady state in which the heavy manufacturing sector's share of GDP would have been 15% lower and aggregate welfare would have been 10% lower than the steady state with successful industrialization. Thus, temporary subsidies for technology adoption had permanent effects.



*Keywords:* Technology adoption, industrialization, knowledge spillover, path dependence
*JEL Codes: O14, O33, O53, R12*



*We are grateful to Andrei A. Levchenko, Dominick Bartelme, Jagadeesh Sivadasan, and Sebastian Sotelo for their guidance and invaluable suggestions and encouragement. We are indebted to Javier Cravino, Alan Deardorff, Kyle Handley, and Linda Tesar for their insightful comments. We thank Maria Aristizabal-Ramírez, Barthélémy Bonadio, Ricardo Hausmann, Yongjun Kim, Bunyada (Mos) Laoprapassorn, Kiminori Matsuyama, Nishaad Rao, Ulrich Schetter, and seminar participants at the Harvard Growth Lab, 2021 Midwest International Trade Meetings, 2021 ETSG, 2021 LACEA-LAMES, and University of Michigan for helpful comments and discussions. We also thank the National Archives of Korea for sharing data. We gratefully acknowledge research support from the Kwanjeong Educational Foundation.


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## 1 Introduction

Large differences in cross-country total factor productivity (TFP) suggest that technology is fundamental to economic development.[1] Based on this observation, economists and policy-makers argue 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 technologies 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 in the post war period, 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 industrialization 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 for those who research late industrialization 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 data set that covers the universe of technology adoption contracts between 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.

[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 spillover and find that knowledge spillover tends to be highly localized (Jaffe et al., 1993; Kerr and Kominers, 2015; Kantor and Whalley, 2019; Moretti, 2019).

[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).

[4]Building on Gerschenkron's (1962) 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).

Using this data set, we can measure firm-level technology adoption directly.

Second, using this novel data set, we provide reduced-form empirical evidence on the firm-level effects of technology adoption. We develop causal estimates of direct 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 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 23 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 1%, 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 Korean government policy of subsidizing technology adoption by domestic 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 a 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 preindustrialized 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 preindustrialized 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 Korea would have evolved had the government not provided subsidies. Our results show that if subsidies had not been provided, 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 been 10% lower, exports would have been 20% lower, and employment would have been 2% 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 (see, among many others, 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, 2019). 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 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 (see, among others, Murphy et al., 1989; 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 Korean government. While Crouzet et al. (2020) studied complementarity in the 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 adoption. The modeling framework of our paper is most closely related to that of Allen et al. (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 (see, among others, Parente and Prescott, 1994; Comin and Hobijn, 2010), 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 the evolution of comparative advantage has been limiteid so far.[6] Using detailed micro data, 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 about new technology in the United States in the nineteenth century. We

[6]For theoretical works, see, among others, Krugman (1987) and Matsuyama (1992) for learning by doing and Buera and Oberfield (2020) and Cai et al. (2021) for knowledge diffusion.

contribute to this literature by quantifying how technology adoption shaped Korea's comparative advantage in heavy manufacturing sectors.

The rest of this paper is organized as follows. Section 2 describes the data we used for our empirical and quantitative analysis. Section 3 describes the historical background of Korea's late industrialization and the Korean government policy that promoted technology adoption. Section 4 presents reduced-form evidence on direct productivity gains to adopters and local productivity spillovers. In Section 5, we build the quantitative model. Section 6 describes how the model can be mapped to the micro data and reduced-form estimates. Section 7 presents quantitative analysis of the Korean government policy. Section 8 concludes the paper.

## 2 Data

We construct our main data set by merging firm-level balance sheet data with data on firms' technology adoption activities. We link these two data sets based on firms' names. The resulting data set include 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 data set is 1970 to 1982. The final data set has 7,223 unique firms of which 49% are heavy manufacturing.

The final data set includes 1,698 contracts made by 628 unique firms.[7] Of these, 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 data set 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 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 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. The law required domestic firms to submit related documents when they signed technology adoption contracts with foreign firms.[10]

[7] There were 1,776 contracts in total in the raw contract data set. However, 78 of them could not be matched with 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 A1 is one page of the contract document between Kolon (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 A2. Also, see Appendix Table A2 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 which played a central role for economic policy-making process in Korea during the sample period.

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

## 3 Historical Background of Late Industrialization in South Korea

In late 1972, the 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]

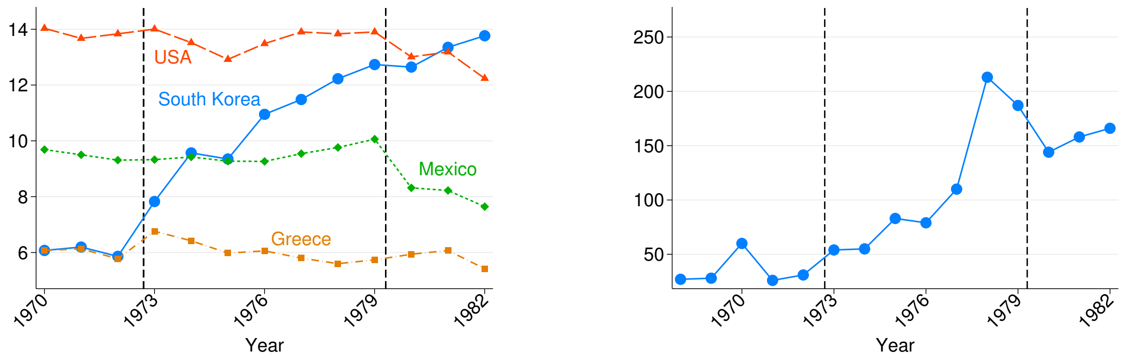
The timing of the policy that subsidized technology adoption and the selection of the targeted sectors were driven by a political shock rather than economic conditions (Lane, 2019).[13] After the Vietnam War, President Nixon changed the diplomatic policy of the United States toward its East Asian allies. 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 US military. He also planned the complete withdrawal of the US 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 US military, the Nixon Doctrine posed a threat for 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

[11]For example, Hyundai Motors, the largest automotive company in 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 import new capital equipment and construct new turnkey plants related to the technologies it had adopted. See Choi and Levchenko (2021) for how the Korean government subsidized firms during the 1970s.

[12]Another commonly used means of technology transfer in developing countries is foreign direct investment (FDI) (Keller, 2004). In Korea, however, FDI did not play a big role. The 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, Korea had a lower stock of FDI. For example, the value of Korea's stock of FDI was only 7 percent of the value of Brazil's stock (Kim, 1997, p.42-43).

[13]In Appendix Section B.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 Korea's HCI Drive.

[14]At the same time, President Park declared martial law and amended the country's constitution into an authoritarian




A. Heavy mfg. share of GDP (%)

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

Figure 1. Late Industrialization and Technology Adoption in Korea

***Notes.*** The two dotted vertical lines represent the start and end of the 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.

government considered Korea's underdeveloped technology in heavy manufacturing sectors as one of the national threats.[15] Given 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 plots the GDP share of the heavy manufacturing sector in Korea and other selected economies. While at the beginning of the period of our analysis, 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 Korean and foreign firms. Our novel data set 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 Korean economy continued to specialize in the heavy

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." (Ministry of Science and Technology, 1972, p. 3)

[16] "Considering our nation's 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)

[17] In Appendix Figure B1, we report heavy manufacturing's share of employment and export and the measure of revealed comparative advantage (Balassa, 1965). Consistent with Figure 1, the employment share increased from 4%

manufacturing sectors.

## 4 Reduced-Form Evidence on Technology Adoption

In this section, we examine how technology adoption benefited 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 Korean firms tend to rely on foreign sources to acquire advanced technologies, whereas small-sized firms 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.

### 4.1 Direct Productivity Gains to Adopters

**Empirical Strategy: Winners vs. Losers 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) that generates 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 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 A3 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,

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 C.4 for historical case studies.

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 D.3 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 $t$,

$$y_{ipt} = \sum_{\tau=\underline{T}}^{\bar{T}} \beta_\tau \times D_{pt}^\tau + \sum_{\tau=\underline{T}}^{\bar{T}} \beta_\tau^{diff} \times D_{pt}^\tau \times \mathbb{1}[Adopt_{it}] + \delta_i + \delta_p + \delta_t + \epsilon_{ipt}, \tag{4.1}$$

where $i$ denotes firm, $p$ pair, and $t$ time. $D_{pt}^\tau$ are event-study variables defined as $D_{pt}^\tau := \mathbb{1}[t-\tau = t(p)]$, where $t(p)$ is event year of pair $p$. $\mathbb{1}[Adopt_{it}]$ is a dummy variable for adoption status. $\delta_i$, $\delta_p$, and $\delta_t$ are firm, pair, and year fixed effects. $\epsilon_{ipt}$ 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.[19] 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.

**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

[19] Appendix Section D.4 describes our revenue TFP estimation procedure in more detail.

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 that chracteristics of foreign firms that made contracts winners and losers to be different. Also, we believe that shocks that satisfy the above conditions were very unlikely. These losers are firms that self-select into the adoption. Negative shocks that hit losers at the time of the event would have caused them not to adopt technology rather than adopt technology from bad foreign firms.

**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 D1) 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 D2, we report the covariate balance test results where we estimate a linear probability model on the effects of pre-event firm observables on an actual adoption status. Across all specifications, none of the estimated coefficients on 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 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 US. We obtain data on patenting activities in the US from the United States Patent and Trademark Office (USPTO). We use firms' patenting activities in the US as a proxy for how these firms are close to the world technology frontier. When these foreign firms made contracts, Appendix Table D3 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 and Figure 2 report the estimated coefficients in Equation (4.1). There as no pre-trend. Winners' sales, revenue TFP, and labor productivity did not begin to increase until adoptions occurred. On average, the adoption increased sales by 51%, revenue TFP by 46%, and labor productivity by 64%.[21]

[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 was 15.54, but the averages of winners of losers were 17.80 and 18.46, respectively (column (2) of Appendix Table A2). Therefore, non-adopters may not represent a valid counterfactual for adopters, and naive comparison between them may lead to biased estimates.

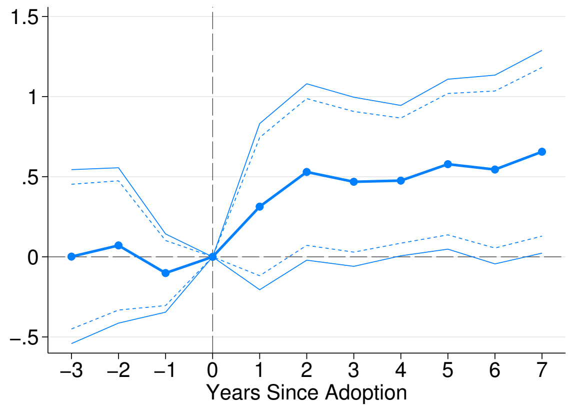
[21] This average is calculated by estimating the following pooled diff-in-diffs model:

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

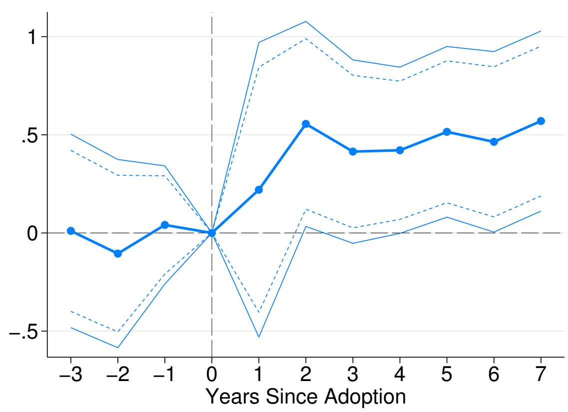
Table 1: Event Study Estimates of Direct Productivity Gains to Adopters: Winners vs. Losers Research Design

| 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 |

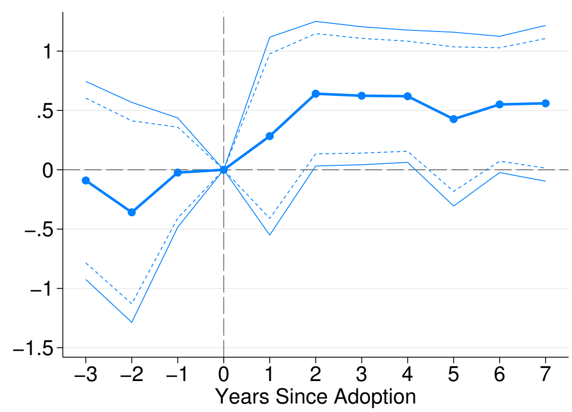
***Notes.*** This table reports the estimated event study coefficients $\beta_\tau^{diff}$ in Equation (4.1) based on the winners vs. losers research design. $\beta_0^{diff}$ is normalized to zero. The dependent variables are log sales, log revenue TFP, and log labor productivity defined as value added 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), log revenue TFP is estimated 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 2. Direct Productivity Gains to Adopters: Winners vs. Losers Design

***Notes.*** This figure illustrates the estimated $\beta_{\tau}^{diff}$ in Equation (4.1) based on winners vs. losers research design. In Panels A, B, and C, the dependent variables are log sales, revenue TFP, and labor productivity. Revenue TFP is estimated based on Wooldridge (2009). Labor productivity is defined as value added per worker. $\beta_{0}^{diff}$ 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. The figure reports 90 and 95 percent confidence intervals based on standard errors two-way clustered at the levels of pairs and firms.

**Robustness.** We run the same regressions using different revenue TFP measures to check for robustness.[22] The results are reported in Appendix Figure D1 and columns (4)-(6) of Table 1. Even though we use different measures, the estimated event study shows no pre-trend, and the estimated coefficients were within a standard error of the estimates of column (3) of Table 1.

We also run the regression using log employment and fixed assets (inputs for production) as dependent variables. The results are reported in Appendix Figure D2. We do not find that winners increase their use of inputs relatively more than losers do after the event. This shows that winners' increases in sales or revenue TFP measures are not input-driven and supports our interpretation of these increases as direct productivity gains to adopters, respectively.

### 4.2 Local Productivity Spillovers to Non-Adopters

In this subsection, we provide empirical evidence on local productivity spillovers of 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:

$$\text{Spill}_{inj(t-h)} = \sum_{k \in nj/\{i\}} \left\{ \frac{(1/dist_{ik})\mathbb{1}[\text{Adopt}_{k(t-h)}]}{\sum\limits_{k' \in nj/\{i\}} (1/dist_{ik'})} \right\}, \tag{4.2}$$

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 $\mathbb{1}[\text{Adopt}_{k(t-h)}]$ 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.[23] The spillover measure captures the fact that

where $Post_{it}$ is an indicator for period $t$ after the event and other variables are defined as in Equation (4.1). We report the average as the estimated coefficient of $\beta^{diff}$. The estimation results are reported in Appendix Table D4.

[22]We use revenue TFP estimates based on Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS.

[23]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,

knowledge spillovers are highly localized and quickly decay with distance. This is supported by the recent empirical evidence on knowledge spillovers (Jaffe et al., 1993; Kerr and Kominers, 2015; Kantor and Whalley, 2019; Moretti, 2019).

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

$$y_{injt} = \beta^S \text{Spill}_{inj(t-h)} + \delta_i + \delta_{njt} + \epsilon_{injt}, \tag{4.3}$$

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

To difference out firm fixed effects, we estimate Equation (4.3) in long-difference:

$$\triangle y_{injt} = \beta^S \triangle \text{Spill}_{inj(t-h)} + \gamma y_{injt_0} + \mathbf{X}'_{injt_0}\boldsymbol{\beta} + \triangle\delta_{njt} + \triangle\epsilon_{injt}, \tag{4.4}$$

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 Korea, large conglomerate groups known as chaebols own multiple firms across sectors and regions. Clustering at the 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 regional and conglomerate levels, this is innocuous. We add dummies for each set of differences and for interaction terms between these dummies and $\delta_{njt}$.

**Identifying Assumption.** Our identifying assumption for a causal interpretation is that distance to adopters within regions and sectors ($\text{Spill}_{inj(t-h)}$) is uncorrelated with the error term $\epsilon_{injt}$ conditional on $\delta_{njt}$, $\delta_i$, 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

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. Under this alternative story, 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).

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, which 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 of $\text{Spill}_{inj(t-h)}$ 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.[24] Because we are controlling for $\delta_{njt}$ and differencing out $\delta_i$, neighboring firms' adoption decisions based on time-varying region-sector factors do not bias our estimates. Only firms' adoption or entry decisions based on time-varying firm-specific factors that are spatially correlated at neighborhood level would bias our estimates.[25] Exploiting spatial variation at a fine level mitigates this potential spatial correlation at neighborhood level within region-sector.

We deal with the second concern by isolating variation in being close to adopters from being close to big-sized firms through controlling for other potential channels of local spatial interactions between firms. We control for the average sales of local firms inversely weighted by the distances similar to Equation (4.2):

$$\ln\Big(\text{Spill-Sales}_{injt}\Big) = \ln\left(\sum_{k\in nj/\{i\}}\left\{\frac{(1/dist_{ik})\text{Sales}_{kt}}{\sum\limits_{k'\in nj/\{i\}}(1/dist_{ik'})}\right\}\right). \tag{4.5}$$

This weighted average sale proxies other agglomeration or competition forces of being close to large-sized firms of the same sector. We also control for a measure of local market access due 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 similar to Donaldson and Hornbeck (2016):

$$\ln\Big(\text{Input-MA}_{injt}\Big) = \ln\left(\sum_{j'}\sum_{k\in nj'/\{i\}}\gamma_j^{j'}(1/dist_{ik})\text{Sales}_{kt}\right), \tag{4.6}$$

where $\gamma_j^{j'}$ are shares of sector $j'$ intermediate inputs used by sector $j$. The market access measure proxies differential market size due to localized input sourcing. Because we do not have information on commodity or service sector firms, we sum $j'$ only across manufacturing sectors.

[24] These new firm that enter between the start and the end of the sample period affect the spillover measure of the continuing firms, but they are not included in the sample, because we are restricting the sample to be firms who were operating at the start of the period.

[25] For example, infrastructure improvement at the neighborhood level that affects both firms' outcomes and adoption decisions would bias our estimates.

Table 2: Local Productivity Spillovers of 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.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by four years. In Panel A, we use the never-adopter sample, which only includes 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 additionally control for adoption status. Dependent variables are log sales and revenue TFP in columns (1)-(5) and (6)-(10), respectively. revenue TFP is estimated based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

**Baseline Results.** Table 2 reports the OLS estimates for $\beta^S$. Column (1) of Panel A is our baseline estimate.[26] The estimated coefficient is statistically significantly positive. One standard deviation increase in the spillover of adoption contributes to 14.5% increases in sales.[27] $\beta^s$ 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. With this interpretation, in this hypothetical region, a 1% increase of a local share of adopters leads to a 4.39% increase in non-adopters' sales. In columns (2), (3), and (4), we additionally control for conglomerate fixed effects, ln(Spill-Sales), and ln(Input-MA), respectively.[28] In column (5), we jointly control for all additional 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.[29] In columns (6)-(10), we use log revenue TFP as a dependent variable.[30] 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 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 4-year lag, we use the spillover measure with 3-year or 5-year lags. The results are reported in Appendix Tables D5 and D6.

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 D9.

Instead of using log sales or revenue TFP, we also use different dependent variables: log fixed assets, assets, and employment, labor productivity. The results are reported in Appendix Tables D7

[26] The magnitude of the estimated coefficients is consistent with the existing 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. The elasticity of the adoption spillover is calculated as follows. The mean level of a 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 percentile 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. The reason why we calculate the elasticity above the 90th percentile is that shares of adopters are highly skewed, where the 75th, 90th, 95th, and 99th percentiles are 0, 0.03, 0.06, and 0.18, respectively.

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

[28] When controlling for conglomerate fixed effects, we categorize independent firms into one single group.

[29] 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 other two spatial interactions operate at broader spatial scale than knowledge spillovers. Then, conditional on $\delta_{njt}$, ln(Spill-Sales) and ln(Input-MA) will not have significant results.

[30] For revenue TFP, there is a smaller number of samples because employment is only available after 1972. We only use one set of differences between 1972 and 1980.

and D8. The estimated coefficients are statistically significant and positive for different dependent variables except for employment.[31]

## 5 Theoretical Framework

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

### 5.1 Setup

We consider a small open economy Home with $N$ regions and $J$ sectors. We divide the world into Home and Foreign. Home is small because 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.[32] 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-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 $\tau^x_{nj} \geq 1$, 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 after incurring fixed adoption costs.

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

### 5.2 Firms

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

$$y_{it} = z_{it} L_{it}^{\gamma_j^L} \prod_{k \in \mathcal{J}} M_{it}^{\gamma_j^k}, \qquad \gamma_j^L + \sum_{k \in \mathcal{J}} \gamma_j^k = 1, \tag{5.1}$$

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

In each region and sector, a final good producer produces non-tradable local sectoral aggregate goods used for final consumption and for intermediate inputs. They are perfectly competitive. A

[31] These results are consistent with the estimates from the winners vs. losers research design where we also find that the adoption increased firms' sales, fixed assets, and productivity measures except for employment.

[32] The small open economy set-up of our model is similar to that of Bartelme et al. (2021).

final goods producer aggregates all available varieties from all regions and countries using a constant elasticity of substitution (CES) aggregator:

$$Q_{njt} = \left[ \sum_{m \in \mathcal{N}} \int_{\omega \in \Omega_{mj}} q_{it}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \int_{\omega \in \Omega_j^f} q_{it}^f(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}}. \tag{5.2}$$

$Q_{njt}$ is the quantity produced of local aggregate sectoral goods. $\Omega_{mj}$ 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 $\omega$ produced by a domestic and foreign firm, respectively. We assume that the available set of Foreign varieties $\Omega_j^f$ is exogenously given to Home 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

$$P_{njt}^{1-\sigma} = \sum_{m \in \mathcal{N}} \left[ \int_{\omega \in \Omega_{mj}} p_{it}(\omega)^{1-\sigma} \right] + (\tau_{nj}^x)^{1-\sigma} \underbrace{\int_{\omega \in \Omega_j^f} p_{it}^f(\omega)^{1-\sigma}}_{=(c_{jt}^f)^{1-\sigma}}, \tag{5.3}$$

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

**Technology Adoption and Export.** In each period, firms make two static decisions: (i) whether to adopt advanced technology and (ii) whether to export after incurring 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. Once firms decide to adopt technology and pay fixed adoption costs, they can increase their productivity (Yeaple, 2005; Lileeva and Trefler, 2010; Bustos, 2011).[33]

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

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

where $\eta > 1$ is direct productivity gains from adoption; $T_{it}$ is a binary adoption decision; $f(\lambda_{njt-1}^T)$

[33] $F_j^T$ is a reduced form parameter that incorporates direct payment to foreign sources, costs of the installation of a new structure, or capital equipment related to a newly adopted technology, and any barriers of 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, the political surroundings of Korea in the 1970s might have affected $F_j^T$. Due to the Cold War, the US government wanted the Korean economy to be self-sustaining and promoted Korea's economic growth. Therefore, it did not block transfers of technology to Korean firms within the free world (Vogel, 1991, p.8).

is a local adoption spillover which increases in a share of adopters in the previous period $\lambda^T_{njt-1}$; and $\phi_{it}$ is exogenous productivity.[34] We allow the spillover to operate with a one-period lag (Allen et al., 2020), which is more realistic given that our focus is the transformation of the Korean economy within 10 years rather than long-run outcomes which have been studied more frequently in the standard trade literature.[35] When making adoption decisions, adopters internalize the direct productivity gain $\eta$, but do not internalize the spillover $f(\lambda^T_{njt-1})$. These externalities make social returns to adoption larger than private returns, which leads to insufficient amounts of adoption than the socially optimum level. For sectors where technology adoption is not available $j \notin \mathcal{J}^T$, firms' productivity only consists of the 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 a semi-elasticity of firm productivity with respect to a local share of adopters. Under this parametrization, we show that $\delta$ can be mapped to the reduced-form spillover estimate in Section 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 historical case studies of Korea in the 1970s.[36] Complete derivations of the microfoundations and related historical cases are described in Appendix C.4.

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

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

[34] This specification implicitly assumes that the direct productivity gains are hicks-neutral, which is supported by empirical evidence. We run the event study regression in Equation (4.1) where a dependent variable is log capital per worker, reported in Appendix Figure D2. We find no changes in log capital per worker after adoption.

[35] Allowing the spillover to operate with a lag makes an economy have a deterministic static equilibrium 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 the other equilibrium in a different period depending on agents' self-fulfilling beliefs. See Krugman (1991) and Matsuyama (1991) for further discussion on self-fulfilling beliefs. Second, because there is a unique static equilibrium for each period, the model can be easily mapped to the cross-sectional data. Multiple static equilibria models in general suffer from identification issues due to multiplicity (Jovanovic, 1989). Kline and Moretti (2014) and Allen et al. (2020) also allowed agglomeration to operate with some lags.

[36] The historical evidence shows that new ideas and tacit knowledge of 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 their knowledge on adopted technologies. This is further supported by higher aggregate labor mobility rates in Korea when compared to Japan and the US in the 1970s (Kim and Topel, 1995). Also, both 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 Serafinelli (2019) for empirical evidence on the effects of labor mobility across firms on knowledge diffusion.

which is parametrized by $\phi_{njt}^{max}$, $\phi_{njt}^{min}$, and $\theta$. We 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 $\kappa$. 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 $\kappa$. This distributional assumption gives us analytical expressions for aggregate variables and rationalizes zeros observed in the data.[37]

**Adoption Subsidy.** The adoption subsidies in Section 3 are modeled as input subsidies because the Korean government provided subsidies to big-sized adopters for purchases of intermediate inputs and new capital equipment related to adopted technologies. Adopters are potentially subject to 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 $\frac{c_{njt}}{\phi_{it} f(\lambda_{njt-1}^T)}$ or $\frac{1-s_{njt}}{\eta} \times \frac{c_{njt}}{\phi_{it} f(\lambda_{njt-1}^T)}$ depending on whether firm $i$ adopts technology or not, respectively. Adopters enjoy a lower unit cost of production than non-adopters because of both higher productivity ($\eta$) and input subsidies ($s_{njt}$).

The government imposes a labor tax $\tau_t^w$ to finance these subsidies.[38] We assume that the labor tax rate is constant across regions, so the after-tax wage in region $n$ is $(1 - \tau_t^w) w_{nt}$. 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 $m$ and Foreign are $q_{inmjt} = (\tilde{p}_{it})^{-\sigma} P_{mjt}^{\sigma-1} E_{mjt}$ and $q_{injt}^x = (\tilde{p}_{it})^{-\sigma} D_{jt}^f$ when firm $i$ charges price $\tilde{p}_{it}$, respectively. A firm optimally charges a constant mark-up $\mu = \sigma/(\sigma - 1)$ over its marginal cost. Thus, prices charged by firm $i$ in region $n$ of sector $j$ selling to region $m$ are $p_{inmjt} = \mu \tau_{nmj} \tilde{c}_{it}$ and export prices are $p_{injt}^x = \mu \tau_{nj}^x \tilde{c}_{it}$.

[37] 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 adopting technology regardless of the values of $F_j^T$. Helpman et al. (2008) also uses truncated Pareto distributional assumption to rationalize zero trade flows across countries.

[38] The assumption that the government finances its adoption subsidies through labor tax is based on the labor market policies and the pro-business attitude of the authoritarian Korean government in the 1970s. The government restricted firms' nominal wage growth to be 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).

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

$$
\begin{aligned}
\pi_{it} = \pi(\phi_{it}) &= \max_{x_{it}, T_{it} \in \{0,1\}} \{\pi(T_{it}, x_{it}; \phi_{it})\} \\
&= \max_{x_{it}, T_{it} \in \{0,1\}} \Bigg\{ \underbrace{\sum_{m \in \mathcal{N}} \left[ \frac{1}{\sigma} \left( \mu \frac{\tau_{nmj}(1-s_{njt})^{T_{it}} c_{njt}}{\phi_{it} \eta^{T_{it}} f(\lambda^T_{njt-1})} \right)^{1-\sigma} P^{\sigma-1}_{mjt} E_{mjt} \right]}_{:=\pi^d(T_{it};\phi_{it}) = \sum_{m\in\mathcal{N}} \pi^m(T_{it};\phi_{it})} \\
&\qquad + x_{it} \Bigg[ \underbrace{\frac{1}{\sigma} \left( \mu \frac{\tau^x_{nj}(1-s_{njt})^{T_{it}} c_{njt}}{\phi_{it} \eta^{T_{it}} f(\lambda^T_{njt-1})} \right)^{1-\sigma} D^f_{jt}}_{:=\pi^x(T_{it};\phi_{it})} - c_{njt} F^x_j \Bigg] - T_{it} c_{njt} F^T_j \Bigg\},
\end{aligned} \tag{5.4}
$$

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 $D^f_{jt}$ are exogenous Foreign demands. $\pi^m(T_{it};\phi_{it})$ are operating profits conditional on adoption status obtained from region $m$ and $\pi^d(T_{it};\phi_{it}) = \sum_{m\in\mathcal{N}} \pi^m(T_{it};\phi_{it})$ are the sum of all these profits from domestic regions. $\pi^x(T_{it};\phi_{it})$ are operating profits in Foreign conditional on adoption status.

**Adoption and Export Cutoff Productivities.** Firms participate in adoption and exporting when the gains from doing so are larger than fixed costs. These net gains from adoption and exporting are higher when firms are more productive. Therefore, with fixed costs, firms' adoption and export decisions are characterized by cutoff productivities, where only firms with productivity above these cutoffs participate in adoption and exporting. We assume that fixed adoption costs are sufficiently higher than fixed export costs so that adopters always export to Foreign.

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

$$
\bar{\phi}^x_{njt} = \frac{\mu c_{njt} (\sigma c_{njt} F^x_j)^{\frac{1}{\sigma-1}}}{f(\lambda^T_{njt-1}) \left( (\tau^x_{nj})^{1-\sigma} D^f_{jt} \right)^{\frac{1}{\sigma-1}}}, \tag{5.5}
$$

and the adoption cutoff $\bar{\phi}^T_{njt}$ is determined at where profits conditional adopting and not adopting are equalized[39]:

$$
\bar{\phi}^T_{njt} = \frac{\mu c_{njt} (\sigma c_{njt} F^T_j)^{\frac{1}{\sigma-1}}}{\left( \left( \frac{\eta}{1-s_{njt}} \right)^{\sigma-1} - 1 \right)^{\frac{1}{\sigma-1}} f(\lambda^T_{njt-1}) \left( \sum_{m\in\mathcal{N}} \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt} + (\tau^x_{nj})^{1-\sigma} D^f_{jt} \right)^{\frac{1}{\sigma-1}}}. \tag{5.6}
$$

[39] $\bar{\phi}^x_{njt}$ and $\bar{\phi}^T_{njt}$ satisfy $\pi^x(T_{it} = 1; \bar{\phi}^x_{njt}) = c_{njt} F^x_j$ and $\pi(T_{it} = 1, x_{it} = 1; \bar{\phi}^T_{njt}) = \pi(T_{it} = 0, x_{it} = 1; \bar{\phi}^T_{njt})$, respectively.

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

$$\lambda^T_{njt} = 1 - G_{njt}(\bar{\phi}^T_{njt}) = \begin{cases} 1 & \text{if} \quad \bar{\phi}^T_{njt} \leq \phi^{min}_{njt} \\ \frac{(\bar{\phi}^T_{njt}/\phi^{min}_{njt})^{-\theta} - \kappa^{-\theta}}{1-\kappa^{-\theta}} & \text{if} \quad \phi^{min}_{njt} < \bar{\phi}^T_{njt} \leq \kappa\phi^{min}_{njt} \\ 0 & \text{if} \quad \bar{\phi}^T_{njt} > \kappa\phi^{min}_{njt}, \end{cases} \tag{5.7}$$

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

**Dynamic Complementarity.** The spillover generates dynamic complementarity in firms' adoption decisions: a higher share of adopters in the previous period increases gains from adoption in the current period. The dynamic complementarity operates through two channels. The first channel comes from complementarity between market size and productivity increases from adoption (Bustos, 2011; Lileeva and Trefler, 2010). Because stronger spillovers increase the productivity of one region relative to other regions, firms in this more productive region will have a larger market size and gains from adoption become larger due to scale effects. This complementarity further incentivizes firms in this more productive region to adopt technology in the current period, which in turn magnifies the spillover force in subsequent periods.

The second channel comes from reduction in 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 make local sectoral aggregate goods cheaper, which in turn makes fixed adoption costs lower (Matsuyama, 1995; Buera et al., 2021). These lowered 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.

### 5.3 Households.

Households make migration and consumption decisions. 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 entry 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).

**Preferences.** Households have Cobb-Douglas preferences over final consumption baskets:

$$u(\{C_{jt}\}_{j\in\mathcal{J}}) = \prod_{j=1}^{J} C^{\alpha_j}_{njt}, \qquad \sum_{j\in\mathcal{J}} \alpha_j = 1, \tag{5.8}$$

where $C_{njt}$ is the consumption of local sector $j$ aggregate goods in region $n$ at period $t$; and $\alpha_j$ is the final good consumption shares. Households are subject to their budget constraints each period: $\sum_{j\in\mathcal{J}} P_{njt}C_{njt} = (1-\tau_t^w+\bar{\pi}_t)w_{nt}$, 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 wage $(1-\tau_t^w)w_{nt}$ and dividends income $\bar{\pi}_t^h w_{nt}$.[40] We denote the ideal price index for households in region $n$ by $P_{nt} = \prod_{j=1}^J P_{njt}^{\alpha_j}$.

**Spatial Mobility.** At the end of the period, households make migration decisions and choose regions to work and live in the next period. After making migration decisions, households supply labor and earn wages. The utility of a household $h$ who lived in region $m$ and moved to region $n$ in period $t$ is

$$\mathcal{U}_{mnt}^h(\epsilon_{nt}^h) = V_{nt} \times \frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}} \times d_{mn} \times \epsilon_{nt}^h, \tag{5.9}$$

where $V_{nt}$ is an exogenous amenity in region $n$; $d_{mn}$ is a moving cost from $m$ to $n$; and $\epsilon_{nt}^h$ is an idiosyncratic preference shock that is independent across households, regions, and periods.

We assume that $\epsilon_{nt}^h$ follows a Fréchet distribution with the shape parameter $\nu$: $\epsilon_t^h \sim F(\epsilon) = exp(\epsilon^{-\nu})$, where $\epsilon_t^h = \{\epsilon_{nt}^h\}_{n\in\mathcal{N}}$ (Eaton and Kortum, 2002). Then, a share of households moving to region $n$ from region $m$ in period $t$ is given by:

$$\mu_{mnt} = \frac{\left(V_{nt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\right)^{\nu}}{\sum_{n'=1}^{N}\left(V_{n't}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{n't}}d_{mn'}\right)^{\nu}}. \tag{5.10}$$

The shape parameter $\nu$ is migration elasticity that governs the responsiveness of migration flows to real income changes of destination.[41] 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:

$$L_{nt} = \sum_{m\in\mathcal{N}} \mu_{mnt}L_{mt-1}. \tag{5.11}$$

**Welfare.** At the of each period, the expected utility of each household of region $n$, prior to realizing idiosyncratic taste shocks $\epsilon_{nt}^h$, is equal to

$$U_{nt} = \mathbb{E}\left[\max_m \left\{\mathcal{U}_{mn,t}^h(\epsilon_{nt}^h)\right\}\right] = \left[\sum_{m\in\mathcal{N}}\left(V_{nt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{nt}}{P_{nt}}d_{mn}\right)^{\nu}\right]^{\frac{1}{\nu}}. \tag{5.12}$$

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

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

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

$$U_t^{agg} = \sum_{n \in \mathcal{N}} \frac{L_{nt-1}}{\sum\limits_{m \in \mathcal{N}} L_{mt-1}} U_{nt}. \tag{5.13}$$

**Aggregate Variables.** For notational convenience, define the average productivity inclusive of 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 $n$. $\bar{\phi}_{njt}^{avg}$ increases in amounts of adoption (lower $\bar{\phi}_{njt}^T$), higher subsidy (higher $s_{njt}$), or higher spillovers (higher $\lambda_{njt-1}^T$). The expression for the average productivity inclusive of subsidies for exporters, $\bar{\phi}_{njt}^{avg,x}$, can be defined similarly, but the difference with $\bar{\phi}_{njt}^{avg}$ is that the lower bound of the distribution is replaced with $\bar{\phi}_{njt}^x$ instead of $\phi_{njt}^{min}$ because of selection effects induced by fixed exporting costs.

Aggregate variables in this economy can be expressed as a function of $\bar{\phi}_{njt}^{avg}$ and $\bar{\phi}_{njt}^{avg,x}$. Because of the distributional assumptions, these aggregate variables admit closed-form expressions.[42] Price index is expressed as:

$$P_{njt}^{1-\sigma} = \sum_{m \in \mathcal{N}} \left[ M_{mj} \left( \frac{\mu \tau_{mnj} c_{mjt}}{\bar{\phi}_{mjt}^{avg}} \right)^{1-\sigma} \right] + (\tau_{nj}^x c_{jt}^f)^{1-\sigma}. \tag{5.14}$$

Region $n$'s share of the total sector $j$ expenditure on goods from domestic region $m$ and from Foreign are expressed as[43]:

$$\pi_{mnjt} = \left( \frac{\tau_{mnj} c_{mjt} / \bar{\phi}_{mjt}^{avg}}{P_{njt}} \right)^{1-\sigma}, \qquad \text{and} \qquad \pi_{njt}^f = \left( \frac{\tau_{nj}^x c_{jt}^f}{P_{njt}} \right)^{1-\sigma}. \tag{5.15}$$

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

$$R_{njt}^d = M_{nj} \left( \frac{\mu c_{njt}}{\bar{\phi}_{njt}^{avg}} \right)^{1-\sigma} \sum_{m \in \mathcal{N}} \tau_{nmj}^{1-\sigma} P_{mjt}^{\sigma-1} E_{mjt}, \qquad \text{and} \qquad R_{njt}^x = M_{njt}^x \left( \frac{\mu \tau_{nj}^x c_{njt}}{\bar{\phi}_{njt}^{avg,x}} \right)^{1-\sigma} D_{jt}^f. \tag{5.16}$$

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

[42] See Appendix Section C.1 for detailed closed-form expressions for aggregate variables and their derivations.

[43] Note that $\sum\limits_{m \in \mathcal{N}} \pi_{nmjt} + \pi_{njt}^f = 1$ holds.

### 5.4 Equilibrium

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

$$\mathbf{\Psi}_t = \{\phi_{njt}^{min}, V_{nt}, D_{jt}^f, c_{jt}^f\}, \qquad \text{and} \qquad \mathbf{s}_t = \{s_{njt}\}.$$

The timing of this model is as follows. Given $\{\lambda_{njt-1}^T, L_{nt-1}\}$, $\mathbf{\Psi}_t$, 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. $\{\lambda_{njt}^T, L_{nt}\}$ that are the outcomes of the static equilibrium in $t$ become the state variables in $t+1$, and so on.

**Static Equilibrium.** Given $\{\lambda_{njt-1}^T\}$, $\{L_{nt-1}\}$, $\mathbf{\Psi}_t$, and $\mathbf{s}_t$, firms maximize profits (Equation (5.4)), households maximize utility (Equation (5.8)), 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:

$$w_{nt}L_{nt} = \left[\sum_{j\in\mathcal{J}} \gamma_j^L \left(\frac{\sigma-1}{\sigma} R_{njt} + M_{njt}^T c_{njt} F_j^T + M_{njt}^x c_{njt} F_j^x\right)\right], \tag{5.17}$$

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:

$$\tau_t^w \sum_{n\in\mathcal{N}} w_{nt}L_{nt} = \sum_{n\in\mathcal{N}} \sum_{j\in\mathcal{J}^T} \left[\frac{\sigma-1}{\sigma} \frac{s_{njt}-1}{s_{njt}} M_{nj} \int_{\bar{\phi}_{njt}^T}^{\kappa\phi_{njt}^{min}} r(\phi_{it}) dG_{njt}(\phi)\right], \tag{5.18}$$

where $r(\phi_{it})$ is firm $i$'s revenues.[44] The left hand and the right-hand sides are the total government tax revenues and spending.

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

$$E_{njt} = \sum_{k\in\mathcal{J}} \gamma_k^j \left(\frac{\sigma-1}{\sigma} R_{nkt} + M_{nkt}^T c_{nkt} F_k^T + M_{nkt}^x c_{nkt} F_k^x\right) + \alpha_j(1 - \tau_t^w + \bar{\pi}_t^h) w_{nt} L_{nt}. \tag{5.19}$$

Goods market clearing implies that region $n$'s total sector $j$ gross output is the sum of the value of

[44] Firm $i$'s revenues in Home and Foreign are proportional to operating profits in Home and Foreign: $r(\phi_{it})^d = \sigma\pi^d(T_{it}^*; \phi_{it})$ and $r(\phi_{it})^x = \sigma\pi^x(T_{it}^*; \phi_{it})$, where $t_{it}^*$ is firm $i$'s optimal adoption decisions. The total revenue $r(\phi_{it})$ is the sum of $r(\phi_{it})^x$ and $r(\phi_{it})^d$.

the total export and the value of the total demand for region $n$'s sector $j$ goods across Home regions:

$$R_{njt} = R^x_{njt} + \sum_{m \in \mathcal{N}} \pi_{nmjt} E_{mjt}. \tag{5.20}$$

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 (5.7) and (5.11), respectively. The law of motion of $\lambda^T_{njt}$ is the key equation of this model. This equation establishes a relationship between $\lambda^T_{njt-1}$ to $\lambda^T_{njt}$ 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 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 (5.4)); (ii) households maximize utility by making consumption decisions (Equation (5.8)); (iii) labor markets clear (Equation (5.17)); (iv) goods markets clear (Equation (5.20)); (v) trade is balanced, and (vi) the government budget is balanced (Equation (5.18));*
- ***(Law of Motion of Dynamic State Variables)*** *(vii)* $\{L_{nt}\}$ *follows the law of motion in Equation (5.11); and (viii)* $\{\lambda^T_{njt}\}_{j \in \mathcal{J}^T}$ *follows the law of motion in Equation (5.7).*

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

### 5.5 Analytical Results: Multiple Steady States

In this subsection, we analytically 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 1.** *(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 1(i)-(iii) are imposed for analytical tractability. Under these assumptions, firms' exogenous productivity follows unbounded Pareto distribution with a normalized location parameter, and firm mass is normalized to be one. Assumptions 1(iv) and (v) are non-trivial. Assumption 1(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 only comes from fixed adoption costs in units of final goods.[45] Assumption (v) is a sufficient condition that guarantees a unique static equilibrium each period.[46]

By combining Equations (5.6) and (5.7), 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 $\lambda_{t-1}^T$. 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[47]:

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

$$\text{where}\quad A(\lambda^T) = \left[\frac{\theta}{\tilde{\bar{\theta}}}\Big((\eta^{\sigma-1}-1)(\lambda^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} \quad \text{and} \quad f(\lambda^T) = exp(\delta\lambda^T). \tag{5.21}$$

The equilibrium share is characterized by the cutoff productivity which is determined at where marginal adopters' net gains from adoption is 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 1(v). Because a static equilibrium is unique each period, there exists a unique sequence of static equilibrium which forms a unique deterministic dynamic path. $\lambda_t^{T*}$ increases in $\lambda_{t-1}^T$ due to dynamic complementarity. $\lambda_t^{T*}$ also increases in two parameters:

[45] With only one region, each firm's increase in productivity due to the spillover is exactly canceled out by competition forces due to other firms' increases in productivity under the CES demand structure. Therefore, the overall increase in productivity through the spillover does not change the relative market size of each firm, nullifying 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 today, which further incentivizes more firms to adopt technology today 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 $\lambda_t^{T*}$ is not affected by $\lambda_{t-1}^T$, because overall productivity increase induced by the spillover increases labor demand, which in turn increases wages and the total fixed adoption cost $w_tF^T$. This is formally stated in Appendix Section C.2.3. Although we assumed that fixed adoption only in units of final goods for simplicity, as long as parts of fixed adoption costs in units of final goods, the model generates dynamic complementarity.

[46] When a fixed adoption cost is in units of final goods, and $\sigma \le 2$ holds, multiple static equilibria can arise each period regardless of the existence of the spillover. This is because firms do not take aggregate price index into account when making adoption decisions. With a larger share of adopters, the aggregate price index becomes lower and this, in turn, decreases the fixed adoption costs and vice versa. This degree of responsiveness of the price index to a share of adopters decreases in the elasticity of substitution $\sigma$. When $\sigma$ 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. These multiple static equilibria are studied by Matsuyama (1995) and Buera et al. (2021). Our model differs from their models because our multiple long-run steady states are generated due to the local spillover. Also, it is natural to assume $\sigma > 2$ because commonly calibrated parameter values for $\sigma$ are larger than 2 (Broda and Weinstein, 2006).

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

$\eta$ and $\delta$. $\eta$ increases $\lambda_t^{T*}$ by increasing marginal adopter's net gains.[48] $\delta$ increases $\lambda_t^{T*}$ by magnifying the 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 $\lambda_{t_0}^T$ determines which steady state is realized in the long-run. These results are summarized in Proposition 1.

**Proposition 1.** *Under Assumption 1,*

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

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

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

*(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 $\eta \in [\underline{\eta}, \bar{\eta}]$;*

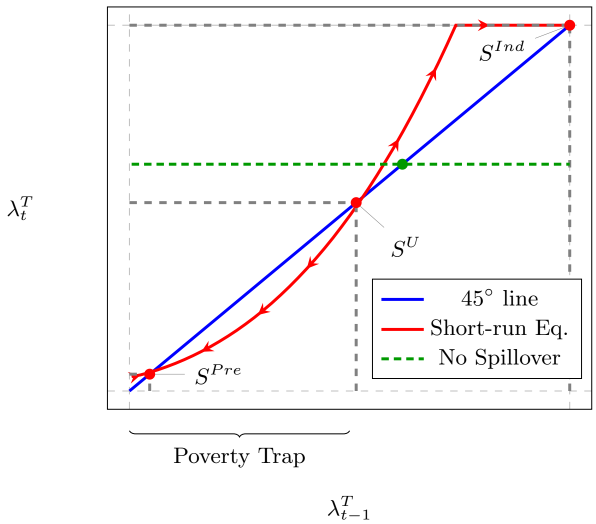
*and (v) (Pareto-Ranked) If there exist multiple steady states, these steady states can be Pareto-ranked based on the equilibrium share of adopters.*

The case of multiple steady states is illustrated in Panel A of Figure 3 where there are three different steady state with two basins of attraction.[49] The red locus is defined by Equation (5.21), where each point of the locus is a short-run equilibrium given $\lambda_{t-1}^T$. Given $\lambda_{t-1}^T$, $\lambda_t^{T*}$ is determined in period $t$ and then in the next period $t+1$, given $\lambda_t^{T*}$, $\lambda_{t+1}^{T*}$ is determined, and so on. Therefore, the equilibrium moves along the red locus as time passes. The steady-state is determined at where $\lambda_{t-1}^{T*} = \lambda_t^{T*}, \forall t$ 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 call the pre-industrialized, the unstable, and the industrialized steady states, respectively.

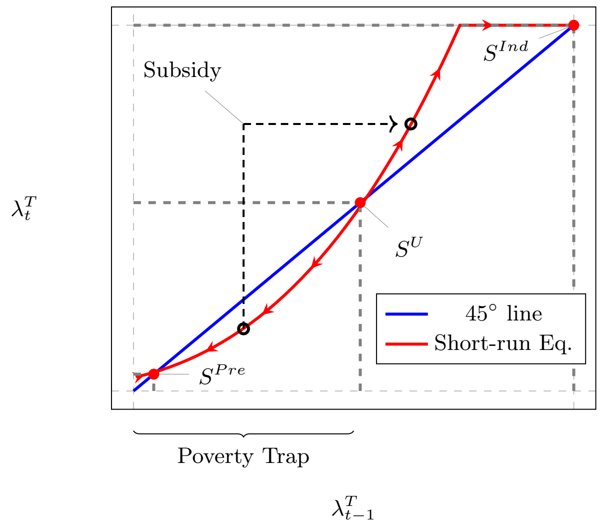
Because technology adoption increases firms' productivity, these steady states can be Pareto-ranked depending on the steady state share of adopters. At $S^{Ind}$, all firms adopt technology, and at

[48] Note that two terms are related to the direct productivity gains governed by $\eta$ in Equation (5.21): $(\eta^{\sigma-1}-1)$ 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 the direct productivity gains. These two general equilibrium effects work in the opposite directions on marginal adopter's net gains from adoption. First, $A(\lambda_t^T)^{1-\sigma}$ captures competition effects, which decreases in $\lambda_t^T$. As more firms adopt technology (increases in $\lambda_t^T$), competitors' productivity increases, which in turn intensifies competition across 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 a price of final goods, and therefore fixed adoption costs (Assumption 1(iv)). Assumption 1(v) ensures that the first general equilibrium effect dominates this second general equilibrium effect.

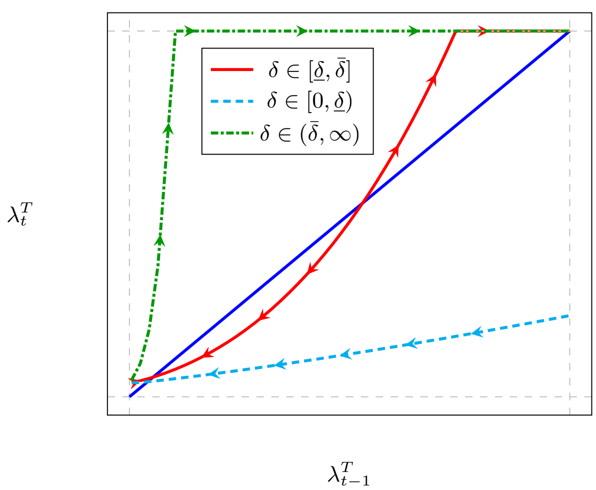
[49] In this economy, there are at most three multiple steady states because of the functional form assumption imposed on the spillover: $f(\lambda_{t-1}^T) = exp(\delta\lambda_{t-1}^T)$. The imposed spillover functional form makes $\lambda_t^T$ to be strictly convex in $\lambda_{t-1}^T$ so that the red locus in Figure 3 intersects with the 45-degree line at most twice. With a functional form assumption that generates a larger degree of nonlinearity, it is possible to have more or less multiple steady states than three.



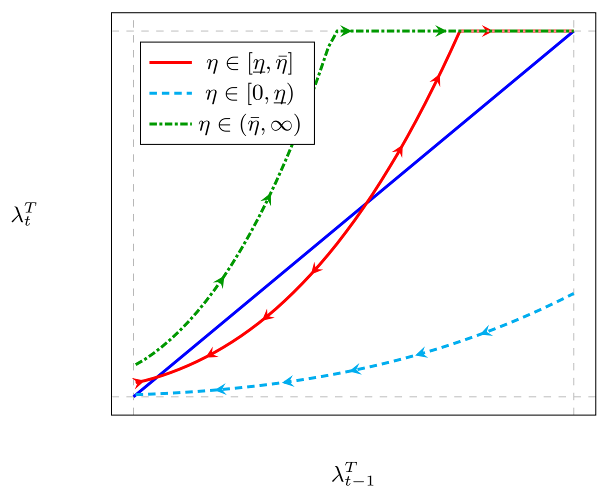

Panel A. Multiple Steady States and Nonlinearity




Panel B. The Role of Adoption Subsidies




Panel C. Comparative Statistics of $\delta$




Panel D. Comparative Statistics of $\eta$

Figure 3. Multiple Steady States and Comparative Statistics

***Notes.*** Panel A illustrates the case when multiple steady states arise and the role of nonlinearity of the short-run equilibrium condition. The multiple steady states arise only when the short-run equilibrium curve is sufficiently nonlinear. Panel B illustrates the role of adoption subsidies. Temporary subsidies can have permanent effects by moving an economy to a new transition path that converges to a higher-productivity steady state $S^{Ind}$. Panels C and D illustrate the comparative statistics of $\delta$ and $\eta$. Multiple steady states arise only for the medium range of values of $\eta$ and $\delta$.

$S^{Pre}$ 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.[50] $S^U$ 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 makes the locus intersect with the 45-degree line multiple period $t$ 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 pinned down by the green dashed horizontal line and the 45-degree line.[51]

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 are not internalizing 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).

**Permanent Effects of Temporary Subsidies and the Multiple Steady States.** When the multiple steady states exist, temporary subsidies for technology adoption in the initial period can have permanent effects by moving an economy that is initially in the poverty trap to a new transition path that converges to the industrialized steady state. This is illustrated in Panel A of Figure 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 Korea's pattern of industrialization toward heavy manufacturing sectors and the temporary policy between 1973 and 1979.

In this model, only the multiple steady states can rationalize the permanent effects of temporary subsidies.[52] When there is only a unique steady state, subsidies temporarily shift the short-run equilibrium curve while subsidies are provided, but the shifted curve moves back to the original position after the end of the subsidies. An economy converges to the original steady state.[53]

**Comparative Statistics.** Proposition 1(iv) implies that the multiple steady states arise only for medium ranges of $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$, that is when the spillover or the 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 a sufficient degree of nonlinearity of the short-run equilibrium locus, making the locus intersect with the 45-degree line only once. This is graphically

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

[51] 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.

[52] Even if there exists a unique steady state, there is room for policy interventions because of the externalities. However, with a unique steady state, these policy interventions should be permanently implemented each period to have permanent effects. This point is graphically illustrated in Appendix Figure C1.

[53] Similarly, Kline and Moretti (2014) studied the Tennessee Valley Authority program in the US and did not detect nonlinearities in the agglomeration elasticity, so they concluded that the program had limited indirect gains through agglomeration.

illustrated in Panels C and D of Figure 3.

The comparative statistics can give one potential explanation on why the Korean economy experienced remarkable transformation toward heavy manufacturing sectors but not other developing countries, although these developing countries benchmarked policies of Korea. Both $\eta$ and $\delta$ can be country-specific and depends on various features of each country.[54] Unlike other developing countries, Korea could have been a special case where its values of $\eta$ and $\delta$ were in a range that generated the existence of multiple steady states.

## 6 Taking the Model to the Data

In our quantitative exercises, we aggregate sectors into four: commodity, light manufacturing, heavy manufacturing, and service sectors. Technology adoption is only available in the heavy manufacturing sector, and the service sector is non-tradable across regions and countries. We also aggregate the data to 42 regions.[55] 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 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 $\Theta$ into two subgroups depending on whether they are externally or internally calibrated:

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

Our calibration procedure proceeds in two steps. In the first step, we externally calibrate $\mathbf{\Theta}^E$ of which $\eta$ and $\delta$ can be mapped to the reduced-form estimates in Section 4 and other remaining parameters are standard in the literature. In the second step, $\mathbf{\Theta}^M$, subsidy $\mathbf{s}_t$, and geographic fundamentals $\mathbf{\Psi}_t$ are internally calibrated using method of moments.

[54] $\eta$ and $\delta$ are generally related to the absorptive capacity of new technology and degree of barriers to knowledge diffusion, respectively. Countries with lower amounts of skilled labor endowments and higher language barriers may have lower values of $\eta$ and $\delta$. When compared to other developing countries, Korea had higher amounts of skilled labor endowment and level of cultural proximity (Rodrik, 1995), which can make Korea have higher values of $\eta$ and $\delta$.

[55] 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 electoral districts.

### 6.1 Externally Calibrated Parameters

**Technology Adoption $\{\eta, \delta\}$.** $\eta$ and $\delta$ are parameters that govern the magnitude of the direct productivity gains and the spillover. The reduced-form estimates of the direct productivity gains and the spillover in Section 4 can be mapped to $\eta$ and $\delta$ of the model. Taking log of adopters' sales, we can derive the following regression model:

$$\log Sales_{it} = (\sigma-1)\log(\eta)T_{it} + \underbrace{\delta\lambda^T_{njt} + \log\Big(\sum_{m\in\mathcal{N}}\tau_{nmj}P^{\sigma-1}_{mjt}E_{mjt} + \tau^x_{nj}D^f_{jt}\Big)}_{\text{Absorbed out by exactly matching on region and sector}} + (\sigma-1)\log\phi_{it},$$

which can be mapped to our winners vs. losers specification (Equation (4.1)). By exactly matching on region and sector, we can absorb out the spillover, a unit cost of production, and the market size that are common across firms within region-sector.[56] Exogenous cancellations by foreign firms can be interpreted as a shock to the fixed adoption cost $F^T_j$ in our model framework that is orthogonal to firms' productivity $\log\phi_{it}$. We calibrate $\eta$ using the average estimates of $\{\beta^{diff}_\tau\}^7_{\tau=1}$ in Equation (4.1) and set $\eta = exp(0.51)/(\sigma-1)$.[57]

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

$$\log Sales_{it} = (\sigma-1)\delta\lambda^T_{njt} + \log\Big(\sum_{m\in\mathcal{N}}\tau_{nmj}P^{\sigma-1}_{mjt}E_{mjt} + \tau^x_{nj}D^f_{j}\Big) + (\sigma-1)\log\phi_{it}.$$

Although the above model-driven regression model is similar to our spillover reduced-form specification (Equation (4.3)), they differ in variation of the spillover within region-sector. $\lambda^T_{njt}$ is common within region-sector in the model, whereas the spillover ($\text{Spill}_{inj(t-h)}$) in Equation (4.3) differs across firms within region-sector depending on their distances to adopters. To connect the model to the data, we rely on the fact that the reduced-form estimates of the spillover can be interpreted as the semi-elasticity of the local share of adopters when distances between firms are all equal. We rely on this interpretation and assume that firms in the model are equally distanced from each other in a finite set of regions. We set $\delta$ to be $4.5/(\sigma-1)$, which is the average value among the spillover estimates in columns (1)-(5) of Table 2.

**Spatial Mobility $\{\nu, d_{mn}\}$.** We parametrize migration costs as a function of the geographic distance: $d_{nm} = dist^\zeta_{nm}\epsilon^d_{nm}$ where $dist_{nm}$ is the geographical distance between regions $n$ and $m$; and $\epsilon^d_{nm}$ is a residual that is not explained by the distance. $\nu$ is set to be 2, which is the estimate from Peters (2019). Using Equation (5.10), we can derive a gravity equation for migration flows. $\zeta$

[56] More precisely, we allow for variation in the spillover in our reduced-form regression model whereas the spillover is assumed to be common across firms within region in our model. 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 ($\text{Spill}_{inj(t-h)} - D^\tau_{pt}$).

[57] 0.51 is based on the pooled diff-in-diffs estimates reported in column (1) of Appendix Table D4.

is externally calibrated by estimating this gravity equation. Using migration flows between 1990 and 1995, we run the following regression model:

$$\log \mu_{nm1990}^{1995} = -\nu\zeta \log dist_{nm} + \delta_m + \delta_n + \epsilon_{mn}^d, \tag{6.1}$$

where $\mu_{nm1990}^{1995}$ are shares of migrants from region $n$ to region $m$; and $\delta_n$ and $\delta_m$ are region fixed effects.[58] To address attenuation bias arising from statistical zeros in the gravity models, we estimate the above equation via pseudo poisson maximum likelihood (PPML) (Silva and Tenreyro, 2006). Under the assumed value for $\nu$, we obtain the value for $\zeta$ from the estimated coefficients. The gravity estimate implies that $\hat{\zeta} = 1.39/\nu$.[59]

**Variable Trade Costs $\{\tau_{nmj}, \tau_{nj}^x\}$.** We parametrize variable internal trade costs as a function of the geographic distance $\tau_{nmj} = (dist_{nm})^\xi$ and assume that $\xi$ is the same across different sectors. We do not observe internal trade flows, so we borrow the estimates from the literature. We take the distance elasticity estimate from Monte et al. (2018) and set $\xi = 1.29/(\sigma - 1)$.[60]

For international trade costs, we assume that to export or import from Foreign, firms have to ship their products to the nearest port and then additionally pay both variable and fixed international trade costs at the port. Under this assumption, international trade costs can be parametrized as $\tau^x = \tilde{\tau}^x \times (dist_n^{port})^\xi$. $\tilde{\tau}^x$ are variable costs incurred at the port. We set $\tilde{\tau}^x$ to be 1.7 following Anderson and Van Wincoop (2004). $(dist_n^{port})^\xi$ are variable costs associated with shipping between region $n$ to the nearest port, where $dist_n^{port}$ is the distance between region $n$ and the port, and $\xi$ is the same parameter of the parametrization of internal trade costs.[61]

**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 $\sigma$ to be 4. We set the Pareto shape parameter $\theta$ to be $1.06 \times (\sigma - 1)$ (Axtell, 2001).[62] We

[58] The estimation procedure is described in detail in Appendix Section E.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 the data availability, regions are aggregated up to 35 regions. $\mu_{nm1990}^{1995}$ is obtained as the total number of migrants moving from region $n$ to region $m$ between 1990 and 1995 divided by the total population of region $n$ in 1990. When computing the total number of population and migrants, we restrict our sample age between 20 and 55.

[59] We find statistically significant results at 1% where we two-way cluster errors at origin and destination levels. The OLS estimates of Equation (6.1) is 1.30 which is similar to 1.39 obtained from PPML. See Appendix Table E2 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) finds the estimated elasticity of Brazilian migration flows to distance is -1.32.

[60] Using internal trade flows within the US, Monte et al. (2018) estimate a distance elasticity of $-1.29$. We calibrate $\xi$ to be $1.29/(\sigma - 1)$.

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

[62] Under the Pareto distributional assumption with shape parameter $\theta$, firm sales distribution follows Pareto distribution with shape parameter $\theta/(\sigma - 1)$. Many previous studies have estimated $\theta$ using firm sales distribution and found

set $M_{nj}$ to be proportional to the GDP share of each region-sector and set $\sum_{n \in \mathcal{N}} M_{nj} = 1$ following Chaney (2008).[63] The Cobb-Douglas shares of preference ($\alpha_j$) and production function ($\gamma_j^k$ and $\gamma_j^L$) are taken from the input-output table in 1972.

### 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 micro 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 $t = 1$.[64] Appendix Section E.2 explains the algorithm of the calibration procedure and how we construct the data inputs in detail.

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

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

$$\text{subject to} \quad \underbrace{\mathbf{C}(\mathbf{\Theta}^M, \mathbf{s}_t, \mathbf{\Psi}_t) = \mathbf{C}_t}_{\text{Aggregate data}}, \quad t \in \{1, 2, 3\}, \quad (6.2)$$

where $\mathbf{W}$ is a weighting matrix; $\mathbf{C}(\mathbf{\Theta}^M, \mathbf{s}_t, \mathbf{\Psi}_t) = \mathbf{C}_t$ are the imposed constraints; $\bar{m}$ and $m(\mathbf{\Theta}^M, \mathbf{s}_t, \mathbf{\Psi}_t)$ are the model moments and data counterparts of the objective function; and $\mathbf{C}(\mathbf{\Theta}^M, \mathbf{s}_t, \mathbf{\Psi}_t)$ 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, corresponding to 1976 and 1980 in the data. Given the lack of information on the distribution of subsidies across regions, we assume that the government provides the same subsidy level $\bar{s}$ across regions in $t = 2, 3$:

$$s_{njt} = \begin{cases} \bar{s} & \text{if} \quad t \in \{2, 3\}, \quad \forall n \in \mathcal{N}, \quad \forall j \in \mathcal{J}^T \cap \mathcal{J}^{policy} \\ 0 & \text{otherwise,} \end{cases} \quad (6.3)$$

that $\theta/(\sigma - 1)$ is close to 1 (Axtell, 2001; di Giovanni et al., 2011; di Giovanni and Levchenko, 2012, 2013).

[63] Chaney (2008) assumes that the total mass of firm of each country is proportional to its total value added in the multi-country setting.

[64] The time interval in the model is 4 years, so 1972, 1976, and 1980 correspond to $t = 1$, $t = 2$, and $t = 3$ of the model periods.

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

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

**Proposition 2.** *(Identifying Moment for Subsidies) Suppose a subsidy plan is given by Equation (6.3). Assume that (a) exogenous firm productivity follows the unbouded 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 $\delta_{nt}$ are region 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 $\eta$, $\delta$, $\sigma$, and $\theta$.*

The proposition shows that sudden increases in shares of adopters in 1980 captured by $\beta^{policy}$ are informative on subsidies, when subsidies are orthogonal to exogenous natural advantages, that is, when $\mathbb{E}[\ln \phi^{min}_{njt} | D^{policy}_{jt}] = 0$ holds. The proposition motivates our approach. Since both in the model and in the data, the simplifying assumptions of Proposition 2 do not hold, we pin down the subsidy level by indirect inference. In particular, using both actual and model-generated data, we estimate the following regression only for the heavy manufacturing sector in 1972 and 1980 via PPML to incorporate zeros:

$$\ln \lambda^T_{n,heavy,t} = \alpha + \beta^{policy} \times D^{policy}_t + \beta_1 \lambda^T_{n,heavy,t-1} + \epsilon_{n,heavy,t}. \tag{6.4}$$

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

Equation (6.4) differs from the regression model in Proposition 2 in two ways. First, because the heavy manufacturing sector is only sector where technology adoption is available in our quantitative exercises, we cannot control for $\delta_{nt}$, and $D^{policy}_t$ cannot be separately identified from time fixed effects.[65] However, we show that $\hat{\beta}^{policy}$ is still informative on $\bar{s}$ in Appendix Section E.4. Second, we

[65] More specifically, we run this regression for shares of adopters in the heavy manufacturing sector in 42 regions for years 1972 and 1980, so we use 84 samples in total. Note that we assumed that (i) technology adoption is only available

control for previous shares rather than subtract them from current shares in dependent variables.[66] The estimated coefficients for $\beta^{policy}$ and $\beta_1$ are 0.65 and 5.62, and statistically significant at the 1% level.[67]

**Objective Function: Micro Moments, $\{\boldsymbol{\Theta}^M, \bar{s}\}$.** We pin down $\boldsymbol{\Theta}^M = \{F_j^T, F_j^x, \kappa\}$ 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 in 1972 and 1980. We identify $\kappa$ using the share of regions with zero adoption in 1972 and 1980. $\kappa$ rationalizes zero adoption in some regions observed in the data. If $\kappa$ is sufficiently low, that is, if the gap between the Pareto lower and upper bound 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. Fixed export costs of the light and heavy manufacturing sectors $F_j^x$ are calibrated to match the median shares of exporters across regions in 1972.[68] Because we do not have detailed data on commodity sector firms, we set fixed export costs of commodity sectors to be the same as those of the light manufacturing sector.

**Constraints: Aggregate Data, $\boldsymbol{\Psi}_t$.** The constraints in Equation (6.2) identify geographic fundamentals $\boldsymbol{\Psi}_t$. We impose the constraints in a way that shares of gross output at region-sector level, aggregate export and import shares, and regional population distribution of the model (Equations (5.10), (5.15), (5.16)) are exactly fitted to the counterpart of the data in 1972, 1976, and 1980. The number of the constraints is the same with the dimension of the geographic fundamentals.[69] Therefore, for any given parameters $\boldsymbol{\Theta}^M$ and subsidy rate $\bar{s}$, 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 inclusive of subsidies $\bar{\phi}_{nj}^{avg}$, following the model-inversion logic from Allen and Arkolakis (2014).[70]

for heavy manufacturing firms and (ii) common subsidies are provided across regions, and (iii) we aggregated heavy manufacturing sectors into one sector when taking 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.

[66] This is because 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.

[67] The value of the estimated coefficient for $\beta_1$ (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 E1.

[68] 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.

[69] 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 where the model is exactly fitted to the region-sector data; $|\mathcal{N}| \times |\mathcal{J}|$ are the number of $\phi_{nj}^{min}$; $|\mathcal{J}^x|$ is the number of $D_j^f$ and $c_j^f$; and $|\mathcal{N}|$ is the number of $V_n$.

[70] By fitting the input-output tables, we can only identify relative productivity differences across regions and sectors, but cannot identify aggregate shifters of productivity. Therefore, while fitting gross output shares at region-sector level, we normalize $\phi_{njt}^{min}$ of one region-sector to be 1 for each period. This is of less concern because our interest is the comparison between the baseline economy to the counterfactual economy, which differences out the common aggregate

Table 3: Calibration Strategy

| Parameters | | | Identification / Moments |
|---|---|---|---|
| | Description | Value | |
| | *External calibration* | | |
| | Structural parameters | | |
| $\eta$ | Direct productivity gains | 1.3 | Winners vs. Losers, Table 2 col. 1 $(\sigma-1)\log(\eta)=0.51$ |
| $\delta$ | Spillover semi-elasticity | 2.25 | Spillover estimate, Table 2 $4.5=(\sigma-1)\delta$ |
| $\sigma$ | Elasticity of substitution | 3 | Broda and Weinstein (2006) |
| $\theta$ | Pareto shape parameter | 2.12 | Axtell (2001), $\theta/(\sigma-1)=1.06$ |
| $\nu$ | Migration elasticity | 2 | Peters (2019) |
| $\zeta$ | Migration cost, $d_{mn}=(dist_{nm})^{\zeta}$ | 0.78 | Gravity estimates |
| $\xi$ | 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) |
| $\alpha_j$ | Preferences | | IO table, 1972 |
| $\gamma^k_j$ | 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. |
| $\kappa$ | Pareto upper bound | 4.42 | # of regions with zero adoption |
| | Geographical fundamentals | | |
| $\phi^{min}_{nj}$ | atural advantage (Pareto lower bound) | | Region-sector sales dist., 1972, 1976, 1980 |
| $D^f_j$ | Foreign market size | | Sectoral export intensity, 1972, 1976, 1980 |
| $c^f_j$ | Foreign imported input price | | 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 (6.4) |

***Notes.*** This table reports calibrated objects of the model, their values, and their identifying moments. The calibration procedure is described in Appendix Section E.2 in more detail.

components.

Table 4: Model Fit

| Moment | Model | Data |
|---|---|---|
| Identifying moment $\hat{\beta}^{policy}$, Equation (6.4) | 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 paraters and their identifying moments in the data.

However, we cannot identify what portion of $\bar{\phi}_{nj}^{avg}$ is attributable to natural advantages $\phi_{nj}^{min}$, shares of adopters $\lambda_{nj}^{T}$, or subsidies $\bar{s}$ from aggregate data alone. To isolate $\phi_{nj}^{min}$, $\lambda_{nj}^{T}$, and $\bar{s}$ separately from $\bar{\phi}_{nj}^{avg}$, we need information on fixed adoption costs $F_{j}^{T}$ and subsidies $\bar{s}$ from the micro moments.

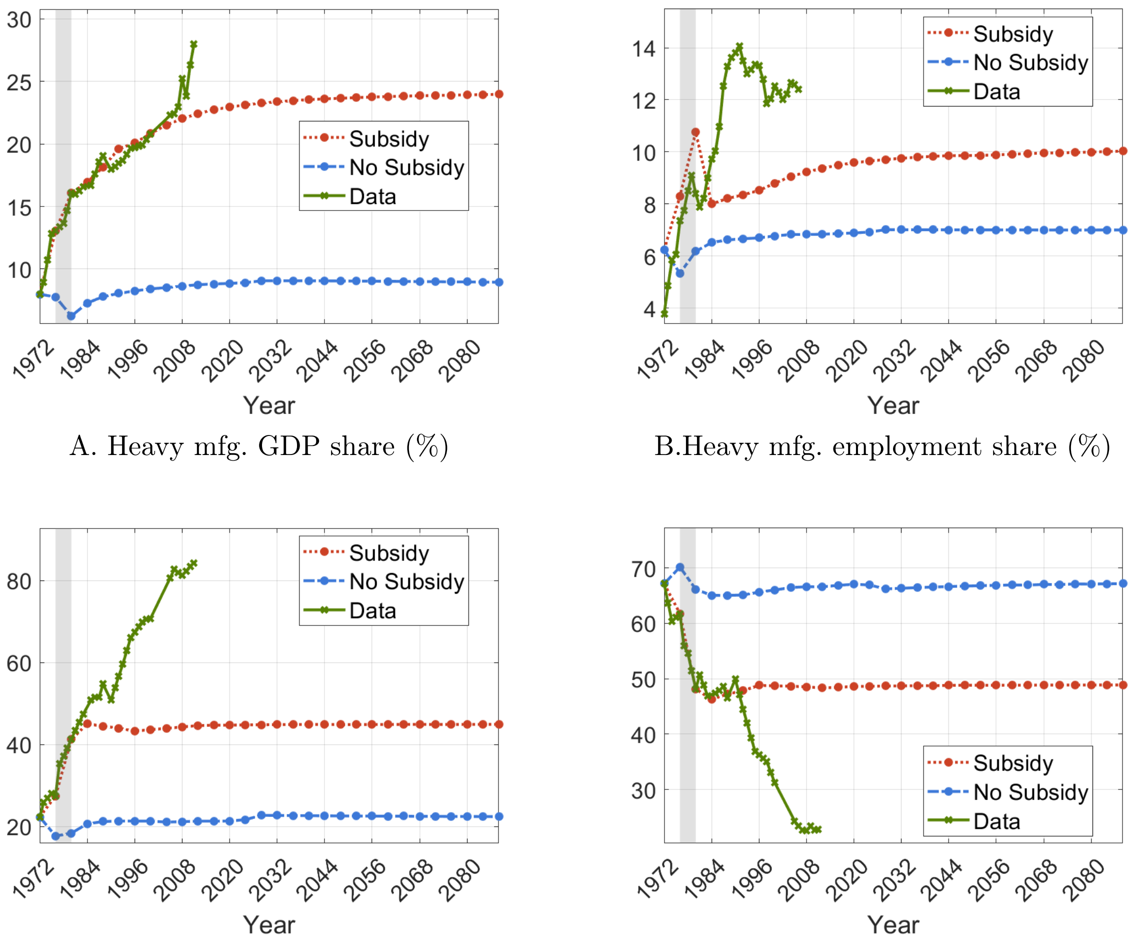
### 6.3 Calibration Results and Model Fit

Table 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, which indicates that adopters are subsidized with 11% of input expenditures. Table 4 reports the model fit. The data moments are well-approximated in the model.

## 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 Korea would have evolved differently if the temporary subsidies had not been provided. We compare the baseline and the counterfactual economies in which the subsidies are provided only in the baseline. Unlike the simplified model where there are at most three steady states in Section 5.5, the full quantitative model potentially admits a larger number of steady states. Which steady state will be reached in the long-run is of a 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 4 reports our main counterfactual results. The red dotted and blue dashed lines plot the equilibrium path of the baseline and counterfactual, respectively. The solid green line depicts the actual path of the Korean economy observed in the data, which is computed from the input-output tables. In Panels A, B, C, and D, we compare the heavy manufacturing sector shares in GDP, em-




A. Heavy mfg. GDP share (%)

B.Heavy mfg. employment share (%)

C. Heavy mfg. export share (%)

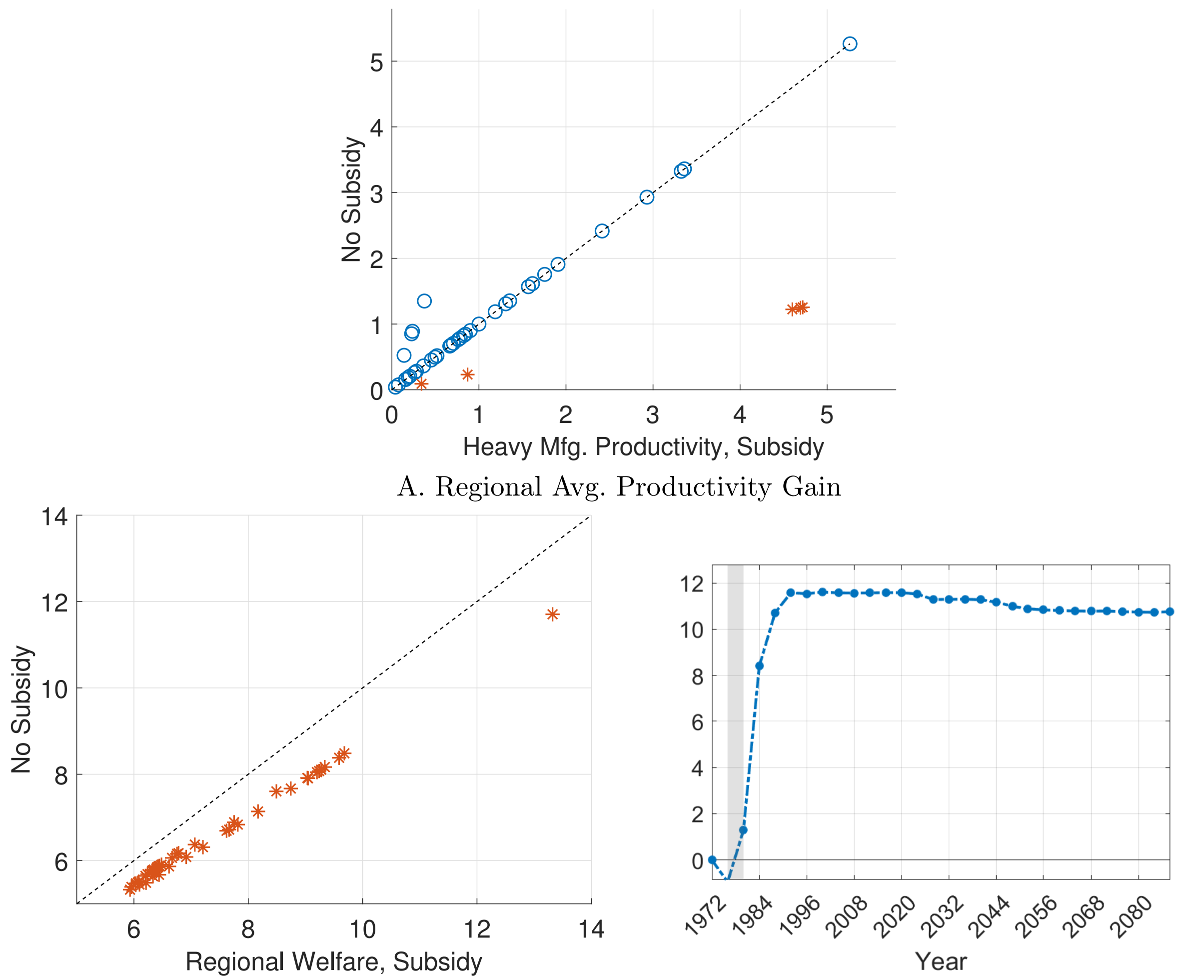
D. Light mfg. export share (%)

Figure 4. Counterfactual results. Industrialization pattern in South Korea when the temporary subsidies had not been provided.

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

ployment, and export, and the light manufacturing sector shares in export. Had not been temporary adoption subsidies provided, Korea's pattern of industrialization and comparative advantage would have evolved differently. Heavy manufacturing GDP, employment, and export shares would have been lower by 15%, 3%, and 22.5% permanently.

Our calibration strategy only fits the cross-section data in 1972, 1976, and 1980 and does not fit the evolution of variables after 1980. Therefore, our model does not explain the evolution of the




A. Regional Avg. Productivity Gain

B. Regional Welfare Gain (%)

C. Aggregate Welfare Gain (%)

Figure 5. Counterfactual Results. Welfare and Regional 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-axis plot each region's average productivity under the baseline and counterfactual economies. Panel B reports regional welfare (Equation (5.12)). The X- and Y-axis 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 (5.13)) of the baseline economy to that of the counterfactual economy.

employment or export shares after 1980 well. However, our model fits the evolution of GDP share of the heavy manufacturing sector quite well even after 1980 (Panel A of Figure 4), which is a non-targeted moment.

Panel A of Figure 5 reports the average productivity changes across regions in the steady state, where the average productivity is defined as $M_{nj}[\int z_{it}(\phi)^{\sigma-1}dG_{njt}(\phi)]^{1/(\sigma-1)}$. Because $M_{nj}$ and $\phi_{njt}^{min}$

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 as the average productivity when $M_{nj}=1, \forall n, j$. X- and Y-axis report the average heavy manufacturing sector productivity of each region under the baseline and counterfactual economies, respectively. Regions that experienced productivity increases due to subsidy-induced technology adoption are colored red. The figure shows that the aggregate industrialization pattern of the baseline economy was driven by large productivity increases of a few regions due to subsidy-induced technology adoption.

Panels B and C of Figure 5 plot the regional and aggregate welfare gains in the baseline economy over the counterfactual economy. On average, the regional and aggregate welfare of the baseline are 10% permanently higher than the counterfactual once the economies reach steady states. 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. Also, note that the beginning of the implementation of the subsidies, the aggregate welfare first decreases in the short run compared to the counterfactual economy because calibrated subsidies are not optimally designed.[71]

**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).[72] 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 E2. While holding other parameters, subsidies, and geographic fundamentals constant, we find that both baseline and counterfactual economies converge to the same steady states.

**Geography: Foreign Market Size and Migration Costs.** We examine how geography interacts with the effects of the temporary adoption subsidies. While comparing the baseline and counterfactual economies with and without the subsidies, we change geographical features of the Korean economy and examine how its long-term effects differ from the main results in Figure 4. We specifically examine the role of Foreign market size and migration costs. We focus on Foreign market size because of large expansion of Korea's exports in the 1960s and 1970s, and narratives that suggest the export expansion played an important role for Korea's economic development.[73] We study migration costs

[71] Analyzing the optimal subsidy in this economy is out of the focus 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.

[72] Heavy manufacturing sectors had disproportionally larger own cost shares of production $\gamma_j^j$ than other sectors. Own cost shares of production were 0.09, 0.26, 0.46, and 0.13 for commodity, light manufacturing, heavy manufacturing, and service sectors, respectively.

[73] Dramatic rapid increases in Korea's exports were outcomes of both 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). Korea also devalued its overvalued currency in 1964, which boosted its exports (Irwin, 2021). Also, the US demands for foreign imports increased

because there were dramatic increases in migration flows from rural to urban areas in Korea during the 1970s, which is a common feature during process of industrialization.[74]

We examine joint implications between Foreign market size and the subsidies. We decreased Foreign market size so that export shares in the heavy manufacturing sector in 1972 was 6.6% which is the level in 1966 (instead of the original 22% in 1972). The results are reported in Appendix Figure E4. The gap of the heavy manufacturing GDP shares between two steady states is about 5%, which is 10% smaller than the main results in Figure 4. These quantitative results provide suggestive evidence that exports might have played an important role in shaping Korea's economic development jointly with subsidies.

We next examine joint implications between migration costs and the subsidies. We set 10% higher migration costs. Because of higher migration costs, people will be moving less toward regions with higher productivity induced by the adoption, which increases wages and costs of production. Due to the complementarity between firm scale and gains from adoption, fewer firms will adopt technology with higher migration costs. These results are reported in Appendix Figure E3. The gap of heavy manufacturing GDP shares between two steady states is around 9%, which is 6% smaller than the main results in Figure 4.

**Comparative Statistics.** We conduct the comparative statistics of $\delta$ and $\eta$ to examine how the particularly chosen parameters drive these multiple steady states results. In Appendix Figure E1, we show that the differences between the outcomes of the baseline and counterfactual economies in the steady states become negligible when either $\delta$ or $\eta$ is too low, consistent with the comparative static results of Proposition 1(iv) in the simplified model.

## 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 the 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 micro 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.

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dramatically between 1960 to 1980. During that period, shares of US imports in the total gross national product rose from 6 to 22%.

[74] According to the World Development Indicators (World Bank), Korea's shares of the rural population decreased from 60 to 40% between 1970 and 1982. Annual shares of migrants to 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).

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 uncertainty 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.

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# APPENDIX

# Appendix A Appendix: Data

## A.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 A1. 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 in 1961 to promote economic development and to 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 became elected as a president of the civilian government. In 1971, he became re-elected, and it was supposed to be his last presidency. In 1972, President Park declared martial law and amended the country's constitution into an authoritarian constitution, called the Yushin constitution, which extended his terms of office for the president indefinitely. After 1961 and until President Park was assassinated in 1979, the EPB was at the center of the economic policy-making process of Korea.

During his presidency, the Foreign Capital Act strictly regulated domestic firms' transactions with foreign firms, including technology adoption contracts. Because of the law, when domestic firms wanted to make technology adoption contracts with foreign firms, they first had to get approvals from the EPB. After the contract, they also had to submit documents related to newly made contracts to the EPB. In these documents, domestic firms had to submit (i) their plans on what to do with newly adopted technologies and (ii) copies of actual contract documents. Starting from 1961, the EPB had monthly meetings until the mid-1980s. In each meeting, they examined newly made transactions between domestic and foreign firms. Documents that were examined in each meeting were collected and preserved by the National Archives of Korea. Our technology adoption data mainly comes from historical contract documents from the National Archives of Korea.

Figure A1 is one example of these documents, which is one page from the actual contract document between Kolon (Korean) and Mitsui Toatsu (Mitsui) (Japanese). Most of the adopted technologies were know-how on construction/operation of plants and capital equipment related to mass production. For example, Figure A1 specifies that Mitsui had to provide blueprints, send skilled engineers to train Korean workers, and provide training service by inviting Korean engineers to its plants in Japan.

**Available Information.** From these contracts, we obtained three main information: (1) domestic firms' names, (2) foreign firms' names, (3) contract years. We use the information on (1) domestic firms' names and (3) contract years to construct a dummy variable of firms' adoption status.

### A.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 produced by the Korea Productivity Center. From the Annual Reports of Korean Companies, we obtain firms' balance sheet variables and locations of production.

**Balance Sheet Variables.** Balance sheet information includes sales, assets, fixed assets, and employment. Employment starts from 1972. We convert all monetary values into 2015 US dollars. The data set covers firm with employment more than 50. Also, the data set has information on firms' start years. We use this start year information to match firms' changes of names.

**Location of Production.** It has detailed information on the address of the location of production. We convert addresses into the 2010 administrative divisions of Korea up to the town level. (We classifies firms' location of production into Li and Dong levels. Then, using distance between towns, we calculate distance between firms within district.

**Sector Groupings.** We classify firms into 10 manufacturing sectors. 4 of them are classified as heavy manufacturing sectors, which mainly follows the sector classification by Lane (2019). Table

A1 reports the classification. This classification is similar to Choi and Levchenko (2021) who use 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.3 Other Data Sets

**Input-Output Tables.** Input-output tables are obtained from Bank of Korea.[75] Input-output tables are available for 1970, 1973, 1975, 1978, 1980, 1983, and 1985 during the sample period.

**OECD Stan Database.** We obtain cross-country heavy manufacturing GDP shares in Figure 1 from OECD Stan database which has sectoral GDP information at 2-digit ISIC3 level.[76]

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 could calculate heavy manufacturing value added shares out of the total manufacturing, but we could not calculate its shares to the national GDP. We supplement the Mexico sample with shares of manufacturing to the total GDP obtained from World Bank Indicators.[77] The share of heavy manufacturing GDP shares is then obtained as value added shares of heavy manufacturing sectors to the total value added of the manufacturing times GDP shares of manufacturing sectors to the total GDP.

### A.4 Criteria for Matching Two Main Data Sets

We match technology adoption and firm balance sheet data sets using firms' names and information on start year and sector. We match two data sets based on the following criteria:

1. Firms should have the same name in a given year.
2. Start years of firms should be prior to observed years of adoption.
    - Even if we observe same names in both data sets, if observed adoption activities happened before start year information in the balance sheet data, we do not match these firms.
3. Firms should be in the same sector.
    - Each contract document has a brief description about technology that firms were adopting.
    - Even if we observe same names in both data sets, if these descriptions do not align with the recorded sector in the balance sheet data, we do not match these firms.

### A.5 Tracking Changes of Firms' Names

One of the key challenges when merging two data sets based on firms' names is that many firms changed their names during the sample period. We track each firm's name using the following steps.

- Step 1: If firms reported their changes of names in the Annual Reports of Korean Companies.
- Step 2: Information on firms' history from their websites

[75] The data were downloaded from https://ecos.bok.or.kr/EIndex_en.jsp.
[76] The data were downloaded from https://stats.oecd.org/Index.aspx?DataSetCode=STAN.
[77] The data were downloaded from https://data.worldbank.org/indicator/NV.IND.MANF.ZS.

Table A1: Classification of Sectors

| | Aggregated Industry | Industry |
|---|---|---|
| Heavy Mfg. | (i) Chemicals, Petrochemicals, Rubber, & Plastic Products | Coke oven products (231)<br>Refined petroleum products (232)<br>Basic chemicals (241)<br>Other chemical products (242)<br>Man-made fibres (243) except for<br>pharmaceuticals and medicine chemicals (2423)<br>Rubber products (251)<br>Plastic products (252) |
| | (ii) Electrical Equipment | Office, accounting, & computing machinery (30)<br>Electrical machinery and apparatus n.e.c. (31)<br>Ratio, television and communication equipment and apparatus (32)<br>Medical, precision, and optical instruments, watches and clocks (33) |
| | (iii) Basic & Fabricated Metals | Basic metals (27)<br>Fabricated metals (28) |
| | (iv) Machinery & Transport Equipment | Machinery and equipment n.e.c. (29)<br>Motor vehicles, trailers and semi trailers (34)<br>Building and repairing of ships and boats (351)<br>Railway and tramway locomotives and rolling stock (352)<br>Aircraft and spacecraft (353)<br>Transport equipment n.e.c. (359) |
| Light Mfg. | (v) Food, Beverages, & Tobacco | Food products and beverages (15)<br>Tobacco products (16) |
| | (vi) Textiles, Apparel, & Leather | Textiles (17)<br>Apparel (18)<br>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)<br>Paper and paper products (21)<br>Publishing and printing (22)<br>Furniture (361) |
| | (ix) Pharmaceuticals & Medicine Chemicals | pharmaceuticals and medicine chemicals (2423) |
| | (x) Other Non-Metallic Mineral Products | Glass and glass products (261)<br>on-metallic mineral products n.e.c. (269) |

- Step 3: Search for firms' names from *https://www.jobkorea.co.kr* or *https://www.saramin.co.kr* if companies' websites are not available.[78]
    - Only when reported start year information in the Annual Reports of Korean Companies coincides with search results from the above two websites, we identify as the same firm.
    - In the case where a firm became merged with other firms, we count such firm as an exit.
- Step 4: Search for newspapers. Newspapers in the 70s sometimes had an article related to changes of firms' names.

### A.6 Coverage.

Figure A2 reports the average coverage of micro 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 in corresponding years. When computing this coverage, for some observations with missing information on sales, we impute using the information on assets. 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 $\beta_j$, we impute missing sales using $\hat{\beta}_j \ln(\text{Assets}_{it})$.

Across sectors, our micro data set covers gross output from the input-output table about 70%. However, there is some heterogeneity across sectors. "Machinery and Transportation Equipment" or "Petrochemical and Chemical" have higher coverage rates, whereas "Food, Beverage, and Tobacco" or "Apparel, Leather, and Textile" are relatively less covered than other sectors.

### A.7 An Example of a Loser

We identify losers from actual contract documents. The Foreign Capital Act also required firms to submit related documents once their contracts failed in the end if these contracts were approved by the EPB. They had to submit official cancellation contract documents between domestic and foreign firms and documents that describe why contracts failed.

Figure A3 reports an example of a loser. Kangwon Industrial Co. (Kangwon) and Broehl Maschinen Fabric GmbH (Broehl) made a contract regarding deck machinery. Broehl was a German firm. Although Kangwon paid fixed fee in advance, Broehl did not sent a blueprint. Panel A is the official English document related to the termination of the contract between two firms. Panel B is the official Korean document in which Kangwon reported why the contract failed in the end to the EPB. The document says that the contract failed because although Kangwon asked Broehl several times for its fulfillment of the contract after Kangwon made the fixed payment, there were no responses from Broehl.

[78] These are two largest job posting websites in Korea.

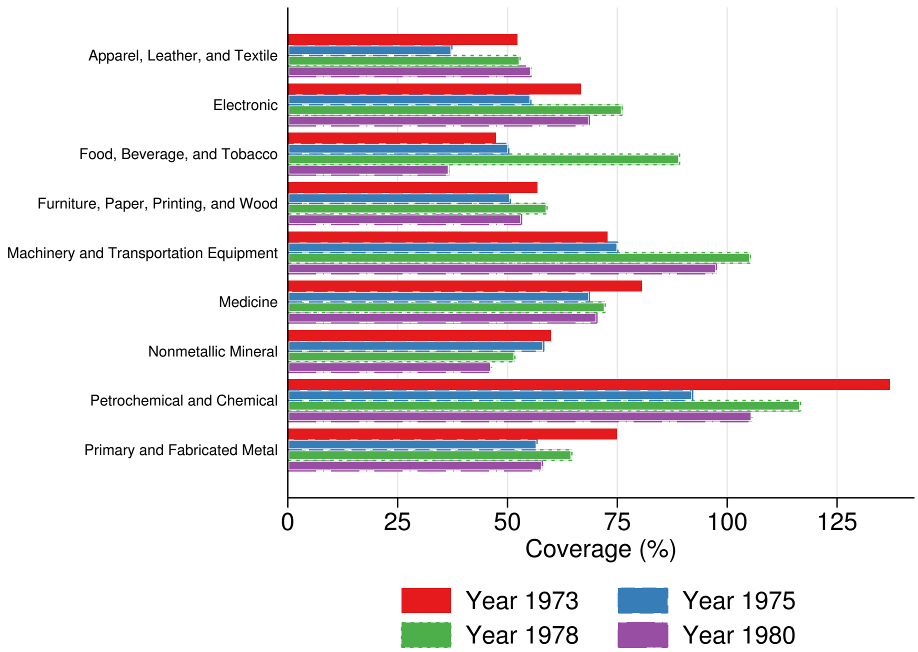
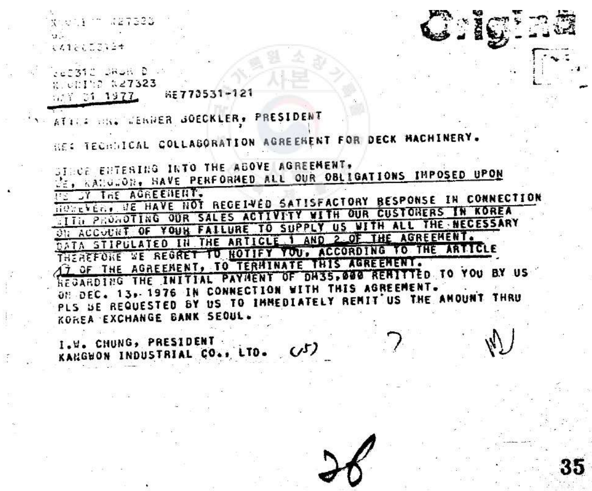



Figure A2. Coverage

***Notes.*** This figure plots ratio between sectoral gross output from the input-output tables and the sum of firms' sales in corresponding sectors.



Original

[illegible] 27323

MAY 31 1977 HE770531-121

ATTN: MR. WERNER GOECKLER, PRESIDENT

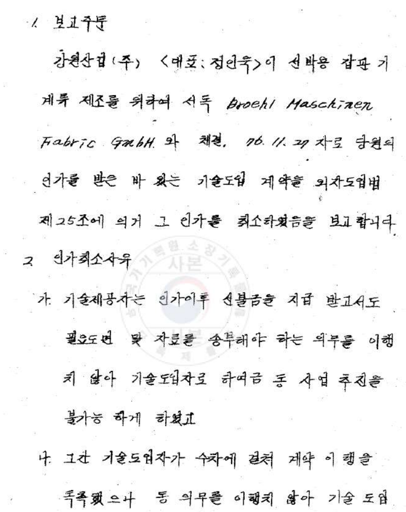
RE: TECHNICAL COLLABORATION AGREEMENT FOR DECK MACHINERY.

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. Official document on termination of the contract between *Kangwon* and *Broehl*



1. 보고주문

강원산업(주) <대표: 정인욱>이 선박용 갑판 기계류 제조를 위하여 서독 Broehl Maschinen Fabric GmbH 와 체결, 76. 11. 27 자로 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. Official document that *Kangwon* reported to the government

Figure A3. Example a Loser. Contract between Kangwon Industrial Co. and Broehl Maschinen Fabric GmbH

### A.8 Descriptive Statistics.

Table A2 reports the descriptive statistics of the constructed data set. 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. $\mathbb{1}[\text{Adopt}]$ is a dummy variable which equals one if a firm is in a contractual relationship with any foreign firms. From the contract data, we can observe when firms made adoption contracts and associated contract years. The dummy variable equals one if a domestic firm is in the middle of contract years. $\mathbb{1}[\text{Adopt}]$ is a dummy variable which equals one if a firm ever adopted foreign technology during the sample period. Consistent with the historical narrative, adoption activities are concentrated among heavy manufacturing firms. Between 1970 and 1982, 13% of heavy manufacturing firms on average adopted technology at least once, whereas it was only 4.2% for light manufacturing firms.

In Panel A of Figure A4, we plot evolution of size of heavy and light manufacturing sectors. Size of sector $j$ is measured as follows:

$$\ln Size_{jt} = \ln\left(\sum_{i \in j} Sale_{it}\right), \qquad j \in \{\text{Light}, \text{Heavy}\}.$$

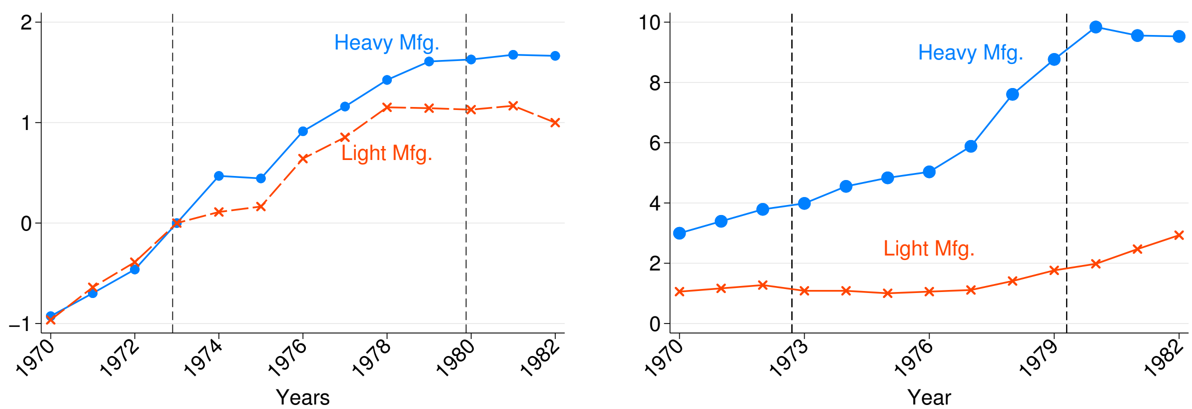
We normalize the size of each sector by their 1973 level so that we can track how heavy and light manufacturing sectors evolved differently after the policy started to be implemented in 1973. In Panel B of Figure A4, we plot shares of adopters in heavy and light manufacturing sectors. The shares are defined as the share of firms who are in contractual relationships with foreign firms to the total number of firms in a given year.

The patterns from the micro data reveal a similar pattern in Figure 1. The total size of heavy manufacturing sectors started increasing faster than that of the light manufacturing sectors after 1973, and this rapid increase coincided with increases in amounts of adoption by heavy manufacturing firms.

Table A2: 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. In column (1), descriptive statistics of all manufacturing firms are reported. In columns (2) and (3), descriptive statistics of heavy and light manufacturing firms are reported. 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.




A. log sum of sales

B. shares of adopters

Figure A4. Evolution of Size of Manufacturing Sectors and Shares of Adopters from the Micro 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 Korean government policy that subsidized technology adoption between 1973 and 1979.

# Appendix B Appendix: Historical Background

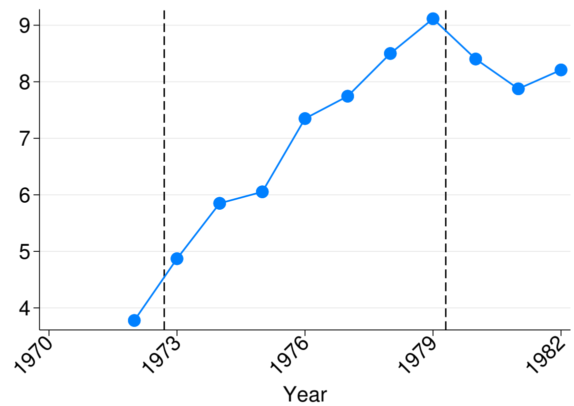
## B.1 Additional Aggregate Statistics on Late Industrialization in South Korea

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 B1, we report the heavy manufacturing employment share, the heavy manufacturing export share, and Balassa's revealed comparative advantage index, which is defined as:

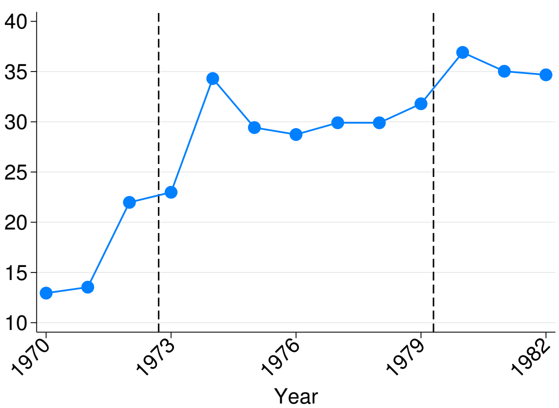
$$RCA_{heavy,t} = \frac{EX^{KOR}_{heavy,t} / \sum_{j \in \mathcal{J}} EX^{KOR}_{jt}}{EX^{RoW}_{heavy,t} / \sum_{j \in \mathcal{J}} EX^{RoW}_{jt}},$$

where $EX^{c}_{jt}$ is the sector $j$ exports of country $c$. The $RCA_{heavy,t}$ measures specialization pattern in the heavy manufacturing sectors of Korea to that of the rest of the world. The employment shares are constructed based on OECD Stan database, and the export shares and the revealed comparative advantage index are computed based on the trade data from Feenstra et al. (2005).[79] Consistent with the heavy manufacturing GDP shares in Figure 1, the employment shares increased from 4 to 8% 1972 and 1982. Korea's sectoral employment data of OECD Stan database starts from 1972, so we could not compute the shares for 1970 and 1971. The export shares increased from 13.7 to 35% between 1970 and 1982.

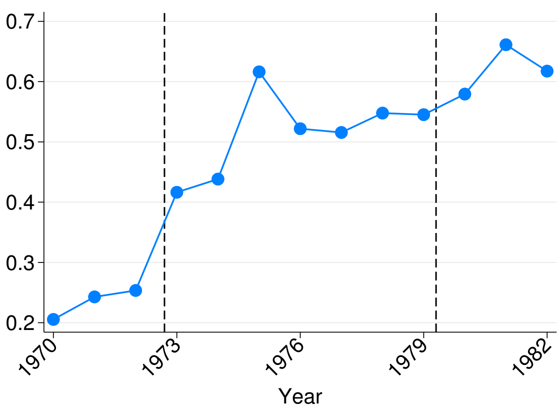
[79]The trade data was downloaded from https://cid.econ.ucdavis.edu/nberus.html.




A. heavy mfg. employment share (%)




B. heavy mfg. export share (%)




C. heavy mfg. Balassa index, RCA

Figure B1. Aggregate Patterns of Late Industrialization in South Korea in the 1970s

***Notes.*** The figure illustrates aggregate changes of the Korean economy during the 1970s. Panels A, B, and C reports heavy manufacturing employment shares, export shares, and Balassa revealed comparative advantage index. The two dotted vertical lines represent the start and the end of the Korean government policy that subsidized technology adoption between 1973 and 1979.

### B.2 The Effects of the Policy on Firms' Technology Adoption Decisions

In this section, we provide empirical evidence on the impact of the Korean government policy on firms' technology adoption decisions. We run the following event study specification for the sample of heavy manufacturing firms:

$$100 \times \mathbb{1}[Adopt_{it}] = \sum_{\tau=-3}^{9} \beta^{\tau} D_t^{\tau} + \delta_i + \epsilon_{it}, \tag{B.1}$$

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 the ease of interpretation. $D_t^{\tau}$ is the event study variables defined as $D_t^{\tau} := \mathbb{1}[t - \tau = 1973]$. $\delta_i$ are time-invariant firm fixed effects. $\epsilon_{it}$ are the error terms. Standard errors are clustered at regional level.

The key variable of interests are $\{\beta^{\tau}\}_{\tau=-3}^{9}$. We normalize $\beta^0$ to be zero. Thus, $\beta^{\tau}$ 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 were driving the implementation of the policy, it 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 restring our samples to be heavy manufacturing firms, time fixed effects are not separately identifiable from these event dummies.

Figure B2 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, only after 1973, more firms started adopting foreign technologies. This sudden rapid increase after 1973 supports the historical narrative of the sudden launch of the HCI Drive driven by the political shock. The estimated coefficients imply that the probability of adopting foreign technology in 1980 increased 20% relative to 1973.

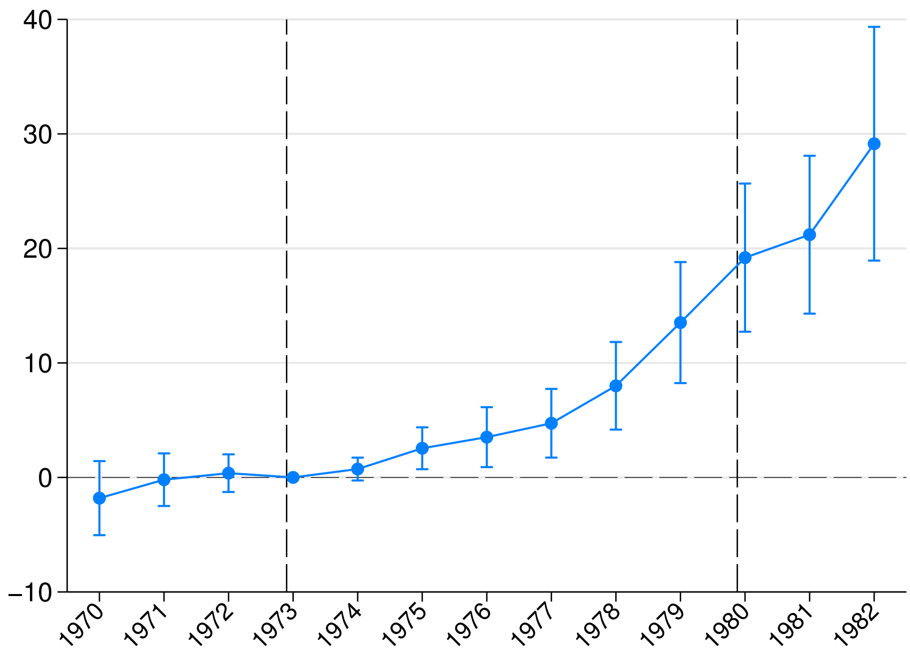



Figure B2. The Impact of the Temporary Subsidies provided by the Korean Government on Firms' Technology Adoption Decisions

***Notes.*** This figure illustrates the estimated $\beta^{\tau}$ in Equation (B.1). $\beta^{0}$ 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 Korean government policy that subsidized technology adoption between 1973 and 1979. Error bars represent 95 percent confidence intervals based on standard errors clustered at regional level.

## Appendix C Appendix: Model

### C.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 the firms' optimal adoption and export decisions and the bounded Pareto distributional assumption, regional-level variables summed across firms within region-sector 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

$$P_{njt}^{1-\sigma} = \sum_{m\in\mathcal{N}} M_{mj}\Bigg\{\underbrace{\int_{\phi_{mjt}^{min}}^{\bar{\phi}_{mjt}^{T}}\left(\frac{\sigma}{\sigma-1}\frac{\tau_{mnj}c_{mjt}}{f(\lambda_{mjt-1}^{T})\phi_{it}}\right)^{1-\sigma} dG_{mjt}(\phi_{it})}_{\text{Non-adopters' varieties}} + \underbrace{\int_{\bar{\phi}_{mjt}^{T}}^{\phi_{mjt}^{max}}\left(\frac{\sigma}{\sigma-1}\frac{\tau_{mnj}(1-s_{mjt})c_{mjt}}{f(\lambda_{mjt-1}^{T})\phi_{it}}\right)^{1-\sigma} dG_{mjt}(\phi_{it})}_{\text{Adopters' varieties}}\Bigg\} + \underbrace{(\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma}}_{\text{Foreign varieties}}.$$

The above equation can be rewritten as:

$$\begin{aligned}
P_{njt}^{1-\sigma} &= \sum_{m\in\mathcal{N}}\Bigg\{M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma}f(\lambda_{mjt-1}^{T})^{\sigma-1}\frac{\theta}{\tilde{\theta}}\frac{1}{1-\kappa^{-\theta}}(\phi_{mjt}^{min})^{\theta} \\
&\quad\times\left[\left((\phi_{mjt}^{min})^{-\tilde{\theta}}-(\bar{\phi}_{mjt}^{T})^{-\tilde{\theta}}\right)+\left(\frac{\eta}{1-s_{mjt}}\right)^{\sigma-1}\left((\bar{\phi}_{mjt}^{T})^{-\tilde{\theta}}-(\phi_{mjt}^{max})^{-\tilde{\theta}}\right)\right]\Bigg\} + (\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma} \\
&= \sum_{m\in\mathcal{N}}\Bigg\{M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma}f(\lambda_{mjt-1}^{T})^{\sigma-1}\frac{\theta}{\tilde{\theta}}\frac{1}{1-\kappa^{-\theta}}(\phi_{mjt}^{min})^{\sigma-1} \\
&\quad\times\left[\left(\left(\frac{\eta}{1-s_{mjt}}\right)^{\sigma-1}-1\right)\left(\frac{\bar{\phi}_{mjt}^{T}}{\phi_{mjt}^{min}}\right)^{-\tilde{\theta}}+\left(1-\left(\frac{\eta}{1-s_{mjt}}\right)^{\sigma-1}\kappa^{-\tilde{\theta}}\right)\right]\Bigg\} + (\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma} \\
&= \sum_{m\in\mathcal{N}}\Bigg\{M_{mj}(\mu\tau_{mnj}c_{mjt})^{1-\sigma} \\
&\quad\underbrace{\times f(\lambda_{mjt-1}^{T})^{\sigma-1}\frac{\theta}{\tilde{\theta}}\frac{1}{1-\kappa^{-\theta}}(\phi_{mjt}^{min})^{\sigma-1}\left[\left(\left(\frac{\eta}{1-s_{mjt}}\right)^{\sigma-1}-1\right)(\tilde{\lambda}_{mjt}^{T})^{\frac{\tilde{\theta}}{\theta}}+\left(1-\left(\frac{\eta}{1-s_{mjt}}\right)^{\sigma-1}\kappa^{-\tilde{\theta}}\right)\right]}_{=\bar{\phi}_{mjt}^{avg}}\Bigg\} \\
&\quad + (\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma},
\end{aligned}$$

where $\tilde{\theta}=\theta-(\sigma-1)$ and $\tilde{\lambda}_{njt}^{T}$. The last equality comes from Equation (5.7).

From the algebra above, a price index can be re-expressed as:

$$P_{njt}^{1-\sigma} = \sum_{m\in\mathcal{N}} \left[ M_{mj} \underbrace{(\mu\tau_{mnj}c_{mjt})^{1-\sigma}}_{\text{Unit cost}} \times \underbrace{(\bar{\phi}_{mjt}^{avg})^{\sigma-1}}_{\substack{\text{Average productivity}\\ \text{inclusive of subsidy}}} \right] + \underbrace{(\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma}}_{\substack{\text{Consumer foreign}\\ \text{market access}}}, \tag{C.1}$$

where

$$\begin{aligned} \bar{\phi}_{njt}^{avg} &= \bar{\phi}^{avg}(\lambda_{njt-1}^{T}, \lambda_{njt}^{T}, s_{njt}, \phi_{njt}^{min}) \\ &= \frac{\theta f(\lambda_{njt-1}^{T})(\phi_{njt}^{min})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})} \left\{ \left( \left( \frac{\eta}{1-s_{njt}} \right)^{\sigma-1} - 1 \right) (\tilde{\lambda}_{njt}^{T})^{\frac{\tilde{\theta}}{\theta}} + \left( 1 - \left( \frac{\eta}{1-s_{njt}} \right)^{\sigma-1} \kappa^{-\tilde{\theta}} \right) \right\}, \end{aligned} \tag{C.2}$$

$\tilde{\lambda}_{njt}^{T} = (1-\kappa^{-\theta})\lambda_{njt}^{T} + \kappa^{-\theta}$, and $\tilde{\theta} = \theta - (\sigma-1)$.[80] A price index depends on the three terms: unit cost, average productivity inclusive of subsidies $\bar{\phi}_{njt}^{avg}$, and consumer foreign market access $(\tau_{nj}^{x}c_{jt}^{f})^{1-\sigma}$. $\bar{\phi}_{njt}^{avg}$ captures how region $n$ can produce sector $j$ intermediate varieties at cheaper cost relative to other regions. Region $n$ can produce at cheaper costs if it has technological advantages ($\lambda_{njt}^{T}$, $\lambda_{njt-1}^{T}$, $\phi_{njt}^{min}$) or higher subsidies ($s_{njt}$). Holding other variables constant, a price index is lower when (i) other neighboring regions have lower unit costs (either lower $\tau_{nmj}$ or $c_{mjt}$), (ii) neighboring regions have higher productivity or obtain more subsidies (higher $\bar{\phi}_{njt}^{avg}$), or (iii) a price of imported inputs is lower (lower $\tau_{nj}^{x}$ or $c_{jt}^{f}$).

The average productivity inclusive of subsidy (Equation (C.2)) increases in a share of adopters in the previous period $\lambda_{njt-1}^{T}$, a share of adopters in the current period $\lambda_{njt}^{T}$, subsidies $s_{njt}$, and a natural advantage captured by the Pareto lower bound $\phi_{njt}^{min}$. A share of adopters in $t-1$ increases average productivity directly through the spillover and indirectly by inducing more firms to adopt technology in period $t$ (Equation (5.7)). A current share of adopters increases the average productivity through direct productivity gains. Subsidies increase the average productivity directly by lowering the cost of production of 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 $R_{njt}^{d}$ and the total value of export $R_{njt}^{x}$: $R_{njt} = R_{njt}^{d} + R_{njt}^{x}$.

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

Regional exports can be written as

$$R^x_{njt} = M_{nj}\Bigg[\int_{\bar{\phi}^T_{njt}}^{\bar{\phi}^{max}_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}(1-s_{njt})c_{njt}}{\eta f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) \\ + \int_{\bar{\phi}^x_{njt}}^{\bar{\phi}^T_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}c_{njt}}{f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it})\Bigg] D^f_{jt}, \quad \text{(C.3)}$$

where the first and the second terms inside the bracket are the total sum of exports by adopters and non-adopters in region-sector $nj$.

The first term inside the bracket can be expressed as:

$$\begin{aligned} &\int_{\bar{\phi}^T_{njt}}^{\bar{\phi}^{max}_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}s_{njt}c_{njt}}{\eta f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) \\ &= \frac{\theta f(\lambda^T_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1}(\phi^{min}_{njt})^{-\theta}\left((\bar{\phi}^T_{njt})^{-\tilde{\theta}} - (\kappa\phi^{min}_{njt})^{-\tilde{\theta}}\right) \qquad \text{(C.4)} \\ &= \frac{\theta f(\lambda^T_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1}(\phi^{min}_{njt})^{\sigma-1}\left((\tilde{\lambda}^T_{njt})^{\frac{\tilde{\theta}}{\theta}} - \kappa^{-\tilde{\theta}}\right), \end{aligned}$$

where $\tilde{\lambda}^T_{njt} = (1-\kappa^{-\theta})\lambda^T_{njt} + \kappa^{-\theta}$. The last equality comes from Equation (5.7).

Similarly, the second term can be re-expressed as:

$$\begin{aligned} &\int_{\bar{\phi}^x_{njt}}^{\bar{\phi}^T_{njt}} \left(\frac{\sigma}{\sigma-1}\frac{\tau^x_{nj}c_{njt}}{f(\lambda^T_{njt-1})\phi_{it}}\right)^{1-\sigma} dG_{njt}(\phi_{it}) \\ &= \frac{\theta f(\lambda^T_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}(\phi^{min}_{njt})^{-\theta}\left((\bar{\phi}^x_{njt})^{-\tilde{\theta}} - (\bar{\phi}^T_{njt})^{-\tilde{\theta}}\right) \qquad \text{(C.5)} \\ &= \frac{\theta f(\lambda^T_{njt-1})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}(\mu c_{njt})^{1-\sigma}(\phi^{min}_{njt})^{\sigma-1}\left((\tilde{\lambda}^x_{njt})^{\frac{\tilde{\theta}}{\theta}} - (\tilde{\lambda}^T_{njt})^{\frac{\tilde{\theta}}{\theta}}\right), \end{aligned}$$

where $\tilde{\lambda}^x_{njt} = (1-\kappa^{-\theta})\lambda^x_{njt} + \kappa^{-\theta}$. The last equality comes from that $\lambda^x_{njt} = 1 - G_{njt}(\bar{\phi}^x_{njt})$.

Using Equations (C.3), (C.4), and (C.5), and $M^x_{njt} = M_{nj} \times \lambda^x_{njt}$, regional exports can be expressed as:

$$R^x_{njt} = M^x_{njt}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg,x}_{njt})^{\sigma-1}}_{\substack{\text{Exporters'} \\ \text{average productivity} \\ \text{inclusive of subsidy}}} \times \underbrace{(\tau^x_{nj})^{1-\sigma} D^f_{jt}}_{\substack{\text{Firm foreign} \\ \text{market access}}},$$

where

$$
\begin{aligned}
\bar{\phi}^{avg,x}_{njt} &= \bar{\phi}^{avg,x}(\lambda^T_{njt-1}, \lambda^T_{njt}, \lambda^x_{njt}, s_{njt}, \phi^{min}_{njt}) \\
&= \frac{\theta f(\lambda^T_{njt-1})(\phi^{min}_{njt})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})} \frac{(\tilde{\lambda}^x_{njt})^{\frac{\tilde{\theta}}{\theta}}}{\lambda^x_{njt}} \\
&\qquad \times \left\{ \left( \left( \frac{\eta}{1-s_{njt}} \right)^{\sigma-1} - 1 \right) \left( \frac{\tilde{\lambda}^T_{njt}}{\tilde{\lambda}^x_{njt}} \right)^{\frac{\tilde{\theta}}{\theta}} + \left( 1 - \left( \frac{\eta}{1-s_{njt}} \right)^{\sigma-1} \kappa^{-\tilde{\theta}} (\tilde{\lambda}^x_{njt})^{-\frac{\tilde{\theta}}{\theta}} \right) \right\},
\end{aligned} \tag{C.6}
$$

$\tilde{\lambda}^x_{njt} = (1-\kappa^{-\theta})\lambda^x_{njt} + \kappa^{-\theta}$, and $\bar{\phi}^{avg,x}_{njt}$ is the exporters' average productivity inclusive of subsidies.

Gross output for domestic expenditures and regional exports are written as:

$$
R^d_{njt} = M_{nj}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg}_{njt})^{\sigma-1}}_{\substack{\text{Average productivity} \\ \text{inclusive of subsidy}}} \times \underbrace{\sum_{m \in \mathcal{N}} \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt}}_{\substack{\text{Firm domestic} \\ \text{market access}}}.
$$

and

$$
R^x_{njt} = M^x_{njt}(\mu c_{njt})^{1-\sigma} \times \underbrace{(\bar{\phi}^{avg,x}_{njt})^{\sigma-1}}_{\substack{\text{Exporters'} \\ \text{average productivity} \\ \text{inclusive of subsidy}}} \times \underbrace{(\tau^x_{nj})^{1-\sigma} D^f_{jt}}_{\substack{\text{Firm foreign} \\ \text{market access}}}.
$$

Both the total domestic sales and exports (i) increase in the average productivities inclusive ob subsidies, (ii) increase in degree of access to markets, (iii) increase in subsidies, and (iv) decrease in the cost of production.

One difference between $\bar{\phi}^{avg,x}_{njt}$ (Equation (C.6)) and $\bar{\phi}^{avg}_{njt}$ (Equation (C.2)) is that $\bar{\phi}^{avg,x}_{njt}$ additionally depends on shares of exporters $\lambda^x_{njt}$. $\lambda^x_{njt}$ 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 $\lambda^x_{njt}$ 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 $\bar{\phi}^{avg}_{njt}$.

### C.2 Analytical Results on Multiple Steady States

#### C.2.1 Derivation of the Equilibrium Share of Adopters in the Simplified Model.

In the simplified model, the cutoff for adoption is expressed as

$$(\bar{\phi}_t^T)^{\sigma-1} = \frac{\sigma P_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma} f(\lambda_{t-1}^T)^{\sigma-1} P_t^{\sigma} Q_t}, \tag{C.7}$$

and the probability of adoption is $\lambda_t^T = (\bar{\phi}_t^T)^{-\theta}$, which can be re-written as

$$(\lambda_t^T)^{-\frac{1}{\theta}} = \bar{\phi}_t^T \tag{C.8}$$

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 monopolistic competition assumption into the above equation, we obtain that $Q_t = [\int z(\omega)^{\sigma-1}d\omega]^{\frac{1}{\sigma-1}}$. Using the Pareto distributional assumption and the cutoff property, we can further derive that

$$\begin{aligned} Q_t = &\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\bar{\phi}_t^T)^{\theta-(\sigma-1)}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T) \\ &= \underbrace{\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}}}_{=A(\lambda_t^T)} \times f(\lambda_{t-1}^T), \end{aligned} \tag{C.9}$$

where the second equality is derived from Equation (C.8). Similarly, using that

$$P_t = [\mu w_t \int z(\omega)^{\sigma-1}d\omega]^{\frac{1}{1-\sigma}},$$

we can derive that

$$\frac{w_t}{P_t} = \frac{w_t}{[\int(\mu w_t/z_{it}(\omega))^{1-\sigma}]^{\frac{1}{1-\sigma}}} = \frac{\sigma-1}{\sigma}\left[\frac{\theta}{\tilde{\tilde{\theta}}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{1-\frac{\sigma-1}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T), \tag{C.10}$$

where the second equality is also derived from Equation (C.8).

Substituting Equations (C.8), (C.9), and (C.10) into Equation (C.7), we can obtain that

$$\lambda_t^T = \left(\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}\times A(\lambda_t^T)^{2-\sigma}\times f(\lambda_{t-1}^T)\right)^{\frac{\theta}{\sigma-1}}. \tag{C.11}$$

Let $\hat{\lambda}_t^T$ be the solution of Equation (C.11). Because the equilibrium share is bounded by 1, the equilibrium share is defined as follows:

$$\lambda_t^T = \begin{cases} \hat{\lambda}_t^T & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\frac{\eta^{\sigma-1}-1}{\sigma F^T} < 1 \\ 1 & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\frac{\eta^{\sigma-1}-1}{\sigma F^T} \geq 1. \end{cases}$$

### C.2.2 Proofs of Proposition 1: Multiple Steady States

**Proof of Proposition 1(i).** The equilibrium is defined by 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 $\lambda_t^T$ but the right hand side strictly decreases in $\lambda_t^T$ due to Assumption 1(v), there exists a unique value of $\lambda_t^T$ that satisfies the above equation. If the obtained $\lambda_t^T$ from the above equation is above 1, $\lambda_t^T = 1$.

□

**Proof of Proposition 1(ii) and (iii).** We prove Proposition 1(ii) and (iii) using the implicit function theorem. Let

$$G(\lambda_t^T;\eta,\delta,\lambda_{t-1}^T) = A(\lambda_t^T)^{2-\sigma}\times f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - (\lambda_t^T)^{\frac{\sigma-1}{\theta}} \tag{C.12}$$

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 of Equation (C.12) with respect to $\lambda_t^T$, we obtain that

$$\begin{aligned}\frac{\partial G}{\partial \lambda_t^T} = \left(\frac{2-\sigma}{\sigma-1}\right) A (\lambda_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\ - \frac{\sigma-1}{\theta}(\lambda_t^T)^{\frac{-\theta+(\sigma-1)}{\theta}} < 0, \end{aligned} \quad \text{(C.13)}$$

where the last inequality comes from $\sigma > 2$ (Assumption 1).

Taking the derivative of Equation (C.12) with respect to $\lambda_{t-1}^T$, we obtain that

$$\frac{\partial G}{\partial \lambda_{t-1}^T} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} exp(\delta \lambda_{t-1}^T)\delta > 0. \quad \text{(C.14)}$$

Applying the implicit function theorem and using the signs of Equations (C.13) and (C.14), we obtain that

$$\frac{\partial \lambda_t^T}{\partial \lambda_{t-1}^T} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \lambda_{t-1}^T} > 0,$$

which proves that $\lambda_t^T$ strictly increases in $\lambda_{t-1}^T$. This proves Proposition 1(ii).

Taking the derivative of Equation (C.12) with respect to $\eta$, we obtain that

$$\begin{aligned}\frac{\partial G}{\partial \eta} &= \left(\frac{2-\sigma}{\sigma-1}\right) A(\lambda_t^T)^{3-2\sigma} f(\lambda_{t-1}^T)\frac{\theta}{\theta-(\sigma-1)}(\lambda_t^T)^{\frac{\theta-(\sigma-1)}{\theta}}(\sigma-1)\eta^{\sigma-2}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\ &\quad + A(\lambda_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T} \\ &= A(\lambda_t^T)^{3-2\sigma} f(\lambda_{t-1}^T)\frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T}\frac{\theta}{\theta-(\sigma-1)}\left[\frac{1}{\sigma-1}(\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\theta}{\theta-(\sigma-1)}}+1\right] > 0. \end{aligned} \quad \text{(C.15)}$$

Taking the derivative of Equation (C.12) with respect to $\delta$, we obtain that

$$\frac{\partial G}{\partial \delta} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} exp(\delta \lambda_{t-1}^T)\lambda_{t-1}^T > 0 \quad \text{(C.16)}$$

Applying the implicit function theorem and using the signs of Equations (C.13), (C.16), and (C.15),

$$\frac{\partial \lambda_t^T}{\partial \eta} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \eta} > 0$$

and

$$\frac{\partial \lambda_t^T}{\partial \delta} = -\frac{\partial G/\partial \lambda_t^T}{\partial G/\partial \delta} > 0.$$

This proves Proposition 1(iii). □

**Proof of Proposition 1(iv).** First, we show that $\lambda_t^T$ is strictly convex in $\lambda_{t-1}^T$. To show the strict convexity, we have to show that $\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} > 0$. We again show this by applying the implicit function theorem and doing some tedious algebra. Applying the implicit function theorem,

$$\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} = -\frac{1}{(\partial G/\partial \lambda_t^T)^3} \\ \times \left[\frac{\partial G}{\partial \lambda_{t-1}^T} \times \left(\frac{\partial G}{\partial \lambda_t^T}\right)^2 - \left(\frac{\partial^2 G}{\partial \lambda_t^T \partial \lambda_{t-1}^T} + \frac{\partial^2 G}{\partial \lambda_{t-1}^T \partial \lambda_t^T}\right) \times \frac{\partial G}{\partial \lambda_{t-1}^T} \times \frac{\partial G}{\partial \lambda_t^T} + \frac{\partial^2 G}{\partial (\lambda_t^T)^2} \times \left(\frac{\partial G}{\partial \lambda_{t-1}^T}\right)^2\right]. \tag{C.17}$$

We examine the sign of each term in the above equation.

$$\frac{\partial^2 G}{\partial (\lambda_{t-1}^T)^2} = A(\lambda_t^T)^{2-\sigma} \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} exp(\delta \lambda_{t-1}^T)\delta^2 > 0. \tag{C.18}$$

$$\frac{\partial^2 G}{\partial \lambda_t^T \partial \lambda_{t-1}^T} = \frac{\partial^2 G}{\partial \lambda_{t-1}^T \partial \lambda_t^T} = \frac{2-\sigma}{\sigma-1} A(\lambda_t^T)^{3-2\sigma} \\ \times \left[\frac{\theta - (\sigma-1)}{\theta}(\eta^{\sigma-1} - 1)(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}\right] exp(\delta \lambda_{t-1}^T)\lambda_{t-1}^T < 0. \tag{C.19}$$

$$\frac{\partial^2 G}{\partial (\lambda_t^T)^2} = \frac{(2-\sigma)(3-\sigma)}{(\sigma-1)^2} A(\lambda_t^T)^{2-2\sigma}\left[\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}(\eta^{\sigma-1}-1)\right]^2 exp(\delta\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\ + \frac{\sigma-2}{\theta} A(\lambda_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}-1} exp(\delta\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\ + \frac{\sigma-1}{\theta}\frac{\theta-(\sigma-1)}{\theta}(\lambda_t^T)^{-\frac{\theta-(\sigma-1)}{\theta}-1} > 0. \tag{C.20}$$

Substituting Equations (C.13), (C.14), (C.18), (C.19), and (C.20) into Equation (C.17), we obtain that $\frac{\partial^2 \lambda_t^T}{\partial(\lambda_{t-1}^T)^2} > 0$, which proves strict convexity.

Because the intercept of $\lambda_t^T$-axis is always positive and $\lambda_t^T$ is strictly increasing and strictly convex in $\lambda_{t-1}^T$, the locus defined by $(\lambda_{t-1}^T, \lambda_t^T)$ that satisfies Equation (5.21) can intersect with the 45 degree line at most twice. [81] Because $\lambda_t^T(\delta, \eta)$ strictly increases in $\delta$ and $\eta$, there exists $\underline{\delta}$ and $\underline{\eta}$ such that the 45 degree line and Equation (C.12) meet at $\lambda_{t-1}^T = 1$. Also, by the same logic, there exits $\bar{\delta}$ and $\bar{\eta}$ such that the 45 degree line is tangent to Equation (C.12). The two lines meet at least twice for $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$.

□

[81] The intercept is always positive because of the unbounded Pareto distributional assumption which guarantees a positive share of adopters at $\lambda_{t-1}^T = 0$.

**Proof of Proposition 1(v).** The welfare of household is $\frac{w_t+\Pi_t}{P_t}$ where $\Pi_t$ is the aggregate profits summed across all firms in the economy.[82] This can be expressed as $\frac{w_t}{P_t}+\frac{\Pi_t}{P_t}$. Using Equations (C.9) and (C.10) and that

$$\frac{\Pi_t}{P_t}=\frac{1}{\sigma}\mu^{1-\sigma}(w_t/P_t)^{1-\sigma}\left[\int_{\omega\in\Omega} z(\omega)^{\sigma-1}d\omega\right]Q_t,$$

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 $\lambda^{T*}$. Therefore, the equilibrium with a larger mass of adopters Pareto-dominates the equilibrium with a smaller mass of adopters.

□

### C.2.3 Source of Dynamic Externality

In this subsection, in the simplified model, we show that the 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 follows:

$$(\bar{\phi}_t^T)^{\sigma-1}=\frac{\sigma w_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma}f(\lambda_{t-1}^T)^{\sigma-1}P_t^{\sigma}Q_t},$$

which is similar to Equation (C.7) but $P_tF^T$ is replaced with $w_tF^T$. $\frac{w_t}{P_t}$ and $Q_t$ are defined analogously to Equations (C.9) and (C.10) regardless of that fixed adoption costs are in units of labor. Substituting Equations (C.9) and (C.10) into the above cutoff, we can derive that

$$\lambda_t^T=\Big(\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}\times\mu\times A(\lambda_t^T)^{1-\sigma}\Big)^{\frac{\theta}{\sigma-1}}. \tag{C.21}$$

The above expression differs from the expression of Equation (C.11) in that $\mu$ replaces $f(\lambda_{t-1}^T)$.

The equilibrium share of adopters in Equation (C.21) shows that the static short-run equilibrium is uniquely determined regardless of values of $\lambda_{t-1}^T$. This is because a fixed adoption cost is in units of labor. Suppose there was a higher share of adopters in the previous period, which increases the overall productivity in $t$. This increase in productivity leads to increases in the overall demand for labor. As labor demands increase equilibrium wage, fixed adoption costs ($w_tF^T$) become higher. In the equilibrium, increases in fixed adoption costs exactly cancel out increases in overall productivity, which in turn makes the equilibrium share of adopters not be affected by $\lambda_{t-1}^T$ (Equation (C.21)).

[82] Note that $L_t=1$.

### C.2.4 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 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 state, and there is only a unique steady-state. For simplicity, we assume that the economy starts at the original steady states in the initial time period.

Figure C1 graphically illustrates that temporary subsidies only have temporary effects when there exists 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 the 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 an economy jumps right 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 the externalities. However, these policy interventions have to be provided permanently to have permanent effects. For example, the new steady state in Figure C1 can be welfare-improving over the original steady state, and this new steady state can be sustained when $\bar{s}$ is permanently provided each period, which is 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 between 1973 and 1979.

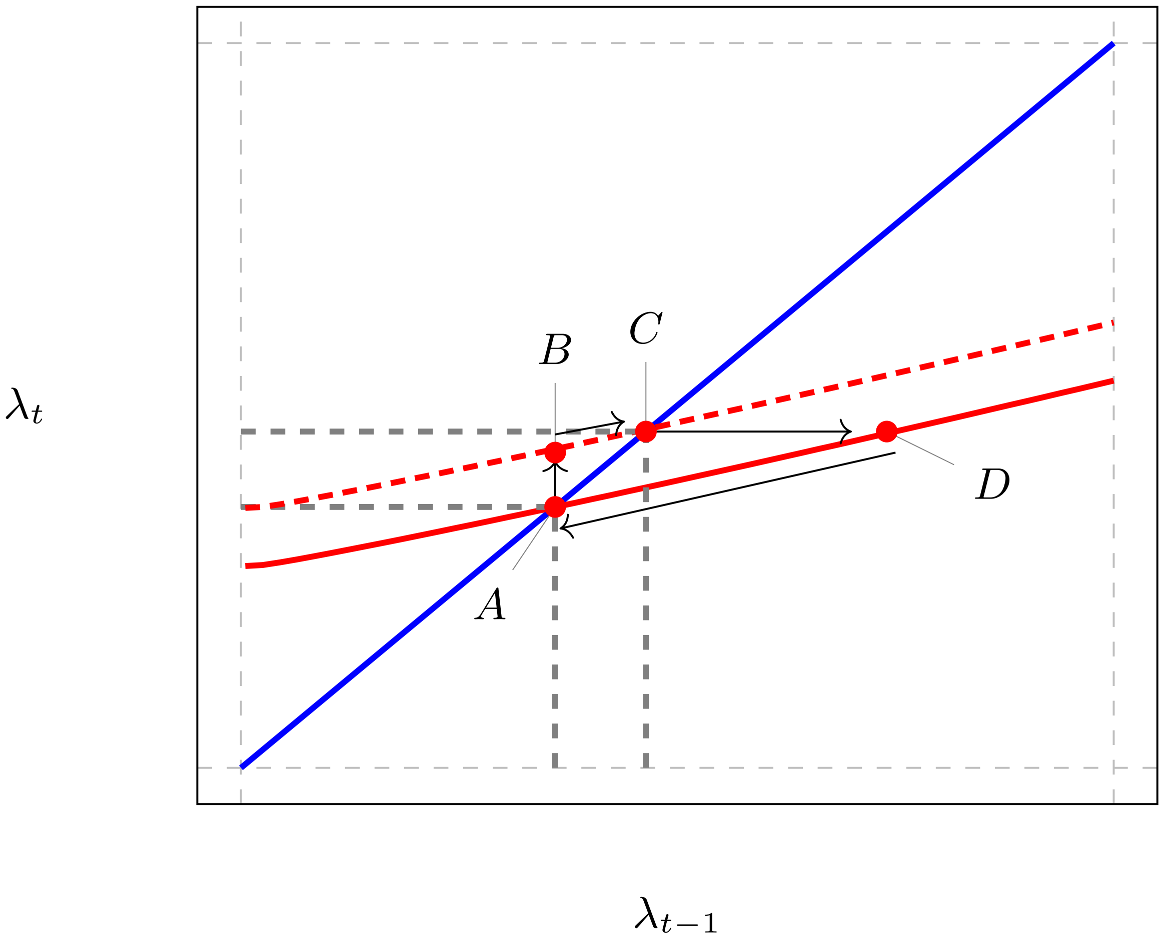



Figure C1. Temporary Subsidies Can Have Permanent Effects Only When Multiple Steady States Exist.

***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.

## C.3 Proof of Proposition 2: Identifying Moment for Subsidies

**Proof of Proposition 2.** 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 $j, j' \in \mathcal{J}^T$.[83] These two assumptions in turn imply that firms in sectors where technology adoption is available face the same market size.

From Equations (5.6) and (5.7), taking log, we can derive the following relationship:

$$\ln \lambda^T_{njt} = \theta\delta\lambda^T_{njt-1} + \underbrace{\frac{\theta}{\sigma-1}\ln\left(\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1} - 1\right)}_{\beta D^{policy}_{jt}}$$
$$\underbrace{-\theta\ln\left(\frac{\mu c_{njt}(\sigma c_{njt}F^T_j)^{\frac{1}{\sigma-1}}}{\left(\sum_{m\in\mathcal{N}} P^{\sigma-1}_{jt}E_{mjt} + D^f_{jt}\right)^{\frac{1}{\sigma-1}}}\right)}_{=\delta_{nt}} + \underbrace{\theta\ln\phi^{min}_{njt}}_{=\epsilon_{njt}}, \quad \text{(C.22)}$$

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 $\delta_{nt}$, and the error term $\epsilon_{njt}$.[84] 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 structure, this is equivalent to $\mathbb{E}[\ln\phi^{min}_{njt}|D^{policy}_{jt}]$ (Equation (C.22)). 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 $\theta$, $\sigma$, and $\eta$, the RHS of the above equation has one-to-one relationship with $\bar{s}$. Therefore , $\bar{s}$ is uniquely identified.

□

[83] $\gamma^k_j = \gamma^k_{j'}$ 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.

[84] Variation in the third term of the RHS across regions comes from wages $w_{nt}$. Note that $c_{njt} = (w_{nt}/\alpha^L_j)^{\alpha^L_j}\prod_{k\in\mathcal{J}}(P_{nkt}/\alpha^k_j)^{\alpha^k_j}$.

### C.4 Possible Microfoundations for Adoption Spillovers

#### C.4.1 Local Diffusion of Knowledge

**Set up.** 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' Profits 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 $a_{it}$:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}, a_{it}\in[0,\infty)} \left\{ \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}} a_{it}^{\gamma_1}\tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma-1}E_t - T_{it}P_tF^T - w_{nt}a_{it}^{\alpha_1}g(\lambda_{nt-1}^T)B_t \right\}, \quad \text{(C.23)}$$

where $T_{it} \in \{0,1\}$ is a dummy variable for adoption status; $\tilde{\eta}$ is the 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, $B_t = b_1P_t^{\sigma-1}E_t$ 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 that a larger share of adopters in the previous period decreases the cost of innovation in the current period. This cost specification captures local diffusion of a non-rivalrous component of ideas. With more firms adopting advanced technologies, other local firms are more likely to learn new ideas from these adopters and can use these newly learned ideas for their own innovation. $g(\lambda_{nt-1}^T)$ captures this local diffusion of ideas in a reduced form. We assume that $\gamma_1(\sigma-1) - \alpha_1 + 1 < 0$ holds.[85]

A firm's optimal choice of $a_{it}$ is characterized by the following first-order condition:

$$\gamma_1(\sigma-1)a_{it}^{\gamma_1(\sigma-1)}\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_{nt}}{\tilde{\eta}^{T_{it}}\tilde{\phi}_{it}}\right)^{1-\sigma} - b_1w_{nt}\alpha_1a_{it}^{\alpha_1-1}g(\lambda_{nt-1}^T) = 0,$$

which gives the optimal level of own innovation $a_{it}^*$

$$a_{it}^* = \bar{C}_{nt}^1 g(\lambda_{nt-1}^T)^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}}(\tilde{\eta}^{T_{it}}\tilde{\phi}_{it})^{\frac{1-\sigma}{\alpha_1-1-\gamma_1(\sigma-1)}},$$

[85] This parameter restriction guarantees the second-order condition of a firm's maximization problem.

where $\bar{C}^1_{nt}$ is a collection of constants and variables that are common within region $n$.[86] Note that $\frac{\delta_{-1}}{\alpha_1-1-\gamma_1(\sigma-1)} > 0$ and $\frac{1-\sigma}{\alpha_1-1-\gamma_1(\sigma-1)} > 0$ hold. This implies that the optimal amounts of innovation is increasing in a share of adopters in the previous period $\lambda^T_{nt-1}$, technology adoption status $T_{it}$, and exogeonus productivity $\tilde{\phi}_{it}$. Substituting the optimal $a^*_{it}$ into Equation (C.23), a firm's maximization problem can be rewritten as:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} \left\{ \frac{1}{\sigma} \left( \frac{\sigma}{\sigma-1} \frac{w_{nt}}{(\bar{C}^1_{nt})^{\gamma_1} g(\lambda^T_{nt-1})^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}} (\tilde{\eta}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}})^{T_{it}} \tilde{\phi}_{it}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}} \right)^{1-\sigma} \times P_t^{\sigma-1} E_t \right.$$
$$\left. - T_{it} P_t F^T \right\}.$$

Note that $g(\lambda^T_{nt-1})^{\frac{-1}{\alpha_1-1-\gamma_1(\sigma-1)}}$ can be mapped to $f(\lambda^T_{nt-1})$, $\tilde{\phi}_{it}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}$ to $\phi_{it}$, and $\tilde{\eta}^{\frac{\alpha_1-\sigma-\gamma_1(\sigma-1)}{\alpha_1-1-\gamma_1(\sigma-1)}}$ to $\eta$ in Equation (5.4) in the main text.

**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 iss considered to be the milestone in the firms' history.

### C.4.2 Learning Externality and Labor Mobility in an Imperfect Labor Market

**Set up.** 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. Managers live two periods, child and adult. They only consume and work in their adulthood. Managers cannot move locations. Once engineers become adults in the second period, they give birth to a child. Managers who worked in firms that adopted technologies pass their knowledge to their children. This learning from parents increases the engineering skills of children when they become adults in the second period, 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 newly born children are 1 and $\gamma_1 > 1$ if parents worked in non-adopters and adopters, respectively.

Following Acemoglu (1996), we assume that engineers and firms are randomly matched one-to-

[86]Specifically, $\bar{C}^1_{nt} = \left[\frac{\sigma b_1 \alpha_1}{\gamma_1(\sigma-1)}\left(\frac{\sigma}{\sigma-1}\right)^{\sigma-1}\right]^{\frac{1}{\gamma_1(\sigma-1)-\alpha_1+1}} w_{nt}^{\frac{\sigma}{\gamma_1(\sigma-1)-\alpha_1+1}}$.

one. The surplus from a match, profits generated by operating firms, is divided by the constant shares between engineers and firms based on Nash bargaining. Managers take the proportion of $\tilde{\beta}$. Once engineers and firms are randomly matched within region, they jointly maximize profits.

A firm makes an adoption decision before the matching happens, so a firm has to make an adoption decision based on its expected profit. A firm's overall productivity depends on (1) exogenous productivity $\tilde{\phi}_{it}$ iid drawn each period, (2) engineering skills of matched engineers, and (3) adoption decisions.

**Firms' Profits Maximization Problem.** Because of the random matching, firms are matched with engineers with higher engineering skills $\gamma_1$ with the probability of $\lambda^T_{nt-1}$ and with engineers with lower skills 1 with the probability of $1-\lambda^T_{nt-1}$.

A firm's maximization problem can be written as

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} (1-\tilde{\beta}) \left\{ \lambda^T_{nt-1} \frac{1}{\sigma} \left( \frac{\sigma}{\sigma-1} \frac{w_{nt}}{\tilde{\eta}^{T_{it}} \gamma_1 \tilde{\phi}_{it}} \right)^{1-\sigma} P_t^{\sigma-1} E_t \right. \\ \left. + (1-\lambda^T_{nt-1}) \frac{1}{\sigma} \left( \frac{\sigma}{\sigma-1} \frac{w_{nt}}{\tilde{\eta}^{T_{it}} \tilde{\phi}_{it}} \right)^{1-\sigma} P_t^{\sigma-1} E_t - P_t F^T T_{it} \right\},$$

where $\lambda_{nt-1}$ 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; $\gamma_1$ is engineering skills of engineers whose parents worked in firms that adopted foreign technology; and $\tilde{\eta}$ is the direct productivity gain from adoption. Doing some algebra, the above maximization problem 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 a local share of adopters in the previous period, and corresponds to $f(\lambda^T_{njt-1})$ in Equation (5.4) in the main text.

**Historical Case Study.** In the 1970s, labor mobility across firms was high in Korea (Kim and Topel, 1995). The average duration of a job in the manufacturing sector in Korea was around 4 years, which was less than half of the average of the US (9 years).

Consistent with this aggregate statistics from Kim and Topel (1995), Enos and Park (1988, Chapter 7) provides one historical case study on the diffusion of knowledge through labor mobility in steel industry. The Pohang Iron and Steel Company Ltd. (POSCO) was the nation's first integrated steel mill, which started operating in 1973. Given Korea's lack of technology, the imported technology played a significant role for POSCO at the initial stages. 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 quitting POSCO got employed in capital good producing firms located near POSCO. In these capital goods producing firms, the technicians helped them produce capital equipment used in *POSCO*, such as water treatment, dust collection, and the 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 worked in *POSCO*.

Enos and Park (1988, p. 166) provides another example. *Daewoo Heavy Industries Ltd* (henceforth *Daewoo*) built the first diesel engine plant in Korea after adopting technology from *MAN* in West Germany. However, one year after *Daewoo* started operating the plant, *Hyundai Heavy Indstries* (henceforth *Hyundai*) adopted technology from *Perkins* in the US and started producing diesel engine. When newly starting business, *Hyundai* hired skilled engineers from *Daewoo* who already acquired technological know-how and capabilities within *Daewoo* by offering higher salaries. Because of this incident, *Daewoo* lost its skilled worker by 33%.

Both aggregate statistics on labor mobility and two historical case studies support one potential channel of knowledge diffusion through labor mobility.

# Appendix D Appendix: Reduced-Form

## D.1 Additional Tables

Table D1: Descriptive Statistics: Winners vs. Losers Design Samples Between the Year of the Cancellation to 5 Years Prior to 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.*** The table reports the descriptive statistics of the winners vs. losers design samples between the year of the cancellation to 5 years prior to the cancellation. Column (9) reports t-statistics of the mean difference between winners and losers with its p-value in brackets. Sales, fixed assets, and assets are measured in 2015 US dollars. Standard errors are two-way clustered by pair and firm and reported in parenthesis. The number of pairs and firms are 33 and 55. All monetary values are in 2015 US dollars.

Table D2: Covariate Balance Test: Winners vs. Losers Design Samples Between the Year of the Cancellation to 5 Years Prior to 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.*** The table reports the covariate balance tests of the winners vs. losers design samples between the year of the cancellation to 5 years prior to the cancellation. The dependent variable is a dummy variable which 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. The number of pairs and firms are 33 and 55.

Table D3: 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.*** The 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 upto an event year and the number of citations by other patents upto an event year. Standard errors are clustered by pair and reported in parenthesis.

Table D4: Pooled diff-in-diffs Estimates of Direct Productivity Gains to Adopters: Winners vs. Losers Research Design

| Dep. Var. | log sales | log labor productivity | log revenue TFP | | | |
|---|---|---|---|---|---|---|
| | | | W. (2009) | ACF (2015) | LP (2003) | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Post_{it} \times \mathbb{1}[Adopt_{it}]$ | 0.51*** | 0.64** | 0.46*** | 0.62*** | 0.45*** | 0.60*** |
| | (0.17) | (0.25) | (0.16) | (0.20) | (0.16) | (0.20) |
| Adj. $R^2$ | 0.88 | 0.62 | 0.87 | 0.94 | 0.90 | 0.61 |
| # cluster (pair) | 34 | 34 | 34 | 34 | 34 | 34 |
| # cluster (firm) | 57 | 57 | 57 | 57 | 57 | 57 |
| N | 951 | 835 | 827 | 827 | 827 | 827 |

***Notes.*** The table reports the pooled diff-in-diffs estimator based on the winners vs. losers research design. 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), revenue TFPs are estimated based on Wooldridge (2009), Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS. 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 pair and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D5: Local Spillover of 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.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by 3 years. In Panel A, we use the subsample which only include 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 additionall control for adopters' adoption status. Dependent variables are log sales and revenue TFP in columns (1)-(5) and (6)-(10), respectively. Revenue TFP is estimated based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D6: Local Spillover of 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.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by 5 years. In Panel A, we use the subsample which only include 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 additionall control for adopters' adoption status. Dependent variables are log sales and revenue TFP in columns (1)-(5) and (6)-(10), respectively. Revenue TFP is estimated based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D7: Local Spillover of 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) | 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.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by 4 years. In Panel A, we use the subsample which only include 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 additionall control for adopters' adoption status. Dependent variables are log employment and labor productivity in columns (1)-(5) and (6)-(10), respectively. Labor productivity is defined as value added per worker. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D8: Local Spillover of 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 | | ✓ | | | ✓ | | ✓ | | | ✓ |

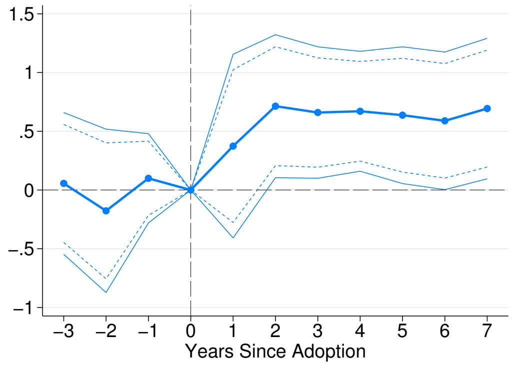
***Notes.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by 4 years. In Panel A, we use the subsample which only include firms that did not adopt any technology until the end of the sample period. In Panel B, we use the full sample including both adopters and non-adopters and additionall control for adopters' adoption status. Dependent variables are log fixed assets and asssets in columns (1)-(5) and (6)-(10), respectively. ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D9: Local Spillover of Technology Adoption: Robustness - Input Market Access

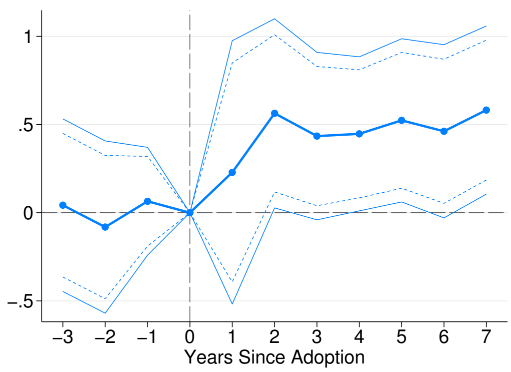
| Dep. Var. | log sales | | log revenue TFP | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Panel A: Never-Adopter Sample* | | | |
| Spill | 4.15*** | 3.97** | 5.36*** | 5.32*** |
| | (1.49) | (1.73) | (1.79) | (1.87) |
| ln(Spill-Sales) | –0.02 | –0.01 | –0.03** | –0.02 |
| | (0.01) | (0.01) | (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.*** The table reports the OLS estimates of Equation (4.4). When constructing the spillover measure defined in Equation (4.2), we lag firms' adoption status by 4 years. In Panel A, we use the subsample which only include 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 additionall control for adopters' adoption status. Dependent variables are log sales and revenue TFP in columns (1)-(2) and (3)-(4), respectively. Revenue TFP is estimated based on Wooldridge (2009). ln(Spill-Sales) and ln(Input-MA) are additional controls defined in Equations (4.5) and (4.6). In all specifications, we control for region-sector fixed effects and initial dependent variable at the start of the sample period. Standard errors are two-way clustered at both region and conglomerate levels and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

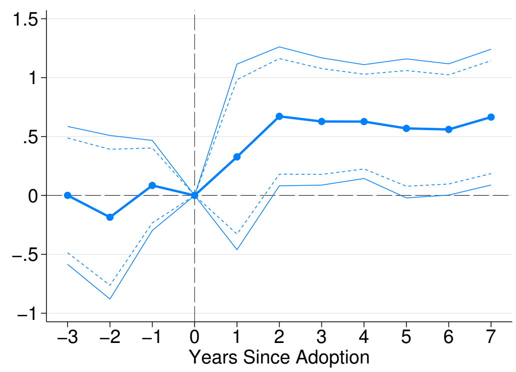
## D.2 Additional Figures




A. log revenue TFP-ACF (2015)



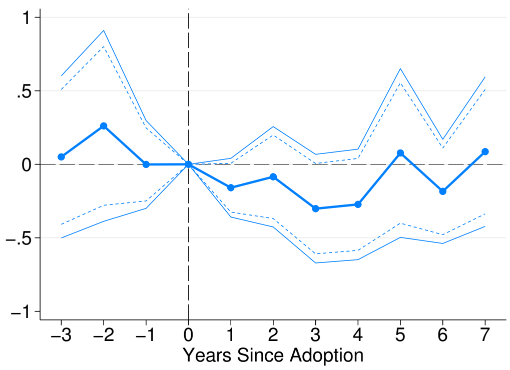

B. log revenue TFP-LP (2003)



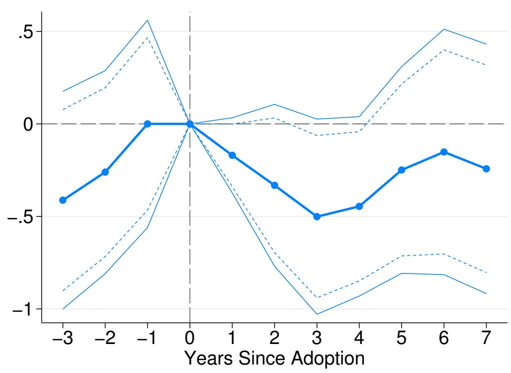

C. log revenue TFP-OLS

Figure D1. Direct Productivity Gains of Technology Adoption: Winners vs. Losers Research Design - Robustness, Alternative TFP measures

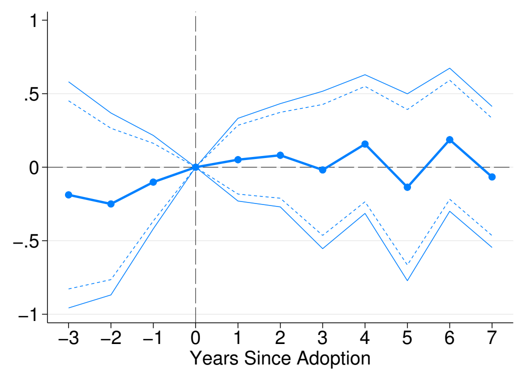
***Notes.*** This figure illustrates the estimated $\beta_{\tau}^{diff}$ in Equation (4.1) based on winners vs. losers research design. The dependent variables are log revenue TFP. In Panels A, B, and C, revenue TFPs are estimated based on Ackerberg et al. (2015), Levinsohn and Petrin (2003), and OLS. $\beta_{0}^{diff}$ is normalized to be 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. log employment




B. log fixed assets




C. log fixed assets per worker

Figure D2. Inputs and Technology Adoption: Winners vs. Losers Research Design

***Notes.*** This figure illustrates the estimated $\beta_{\tau}^{diff}$ in Equation (4.1) when dependent variables are log employment, fixed assets, and fixed assets per worker. $\beta_{0}^{diff}$ is normalized 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.

### D.3 Matching Algorithm

This section describes the matching algorithm used for matching a loser to a winner in Section 4.1. Let $\mathbf{X} \in \mathcal{R}_k$ denotes the k-dimensional observable variables. The matching proceeds in the following 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
   - have the same values of the variables of $\mathbf{X}^e$ with a loser $f$;
   - minimize the Mahalanobis distance with loser $f$ in terms of $\mathbf{X}^d$:

   $$\text{adopter}_g \in \underset{g' \in \mathcal{F}}{\arg\min}\{((\mathbf{X}_f^d - \mathbf{X}_g^d)'\mathbf{S}^{-1}(\mathbf{X}_f^d - \mathbf{X}_g^d)\}$$

   where $\mathcal{F}$ is a set of firms; $\mathbf{S}$ is the sample covariance of $\mathbf{X}^d$; and $\mathbf{X}_f^d$ and $\mathbf{X}_g^d$ are 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.

### D.4 Production Function Estimation

In this section, we discuss the estimation procedure for revenue TFP measures. The revenue TFP measures are obtained as the residuals after estimating the production using different methodologies: Wooldridge (2009), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and OLS. We estimate the following Cobb-Douglas value added production function:

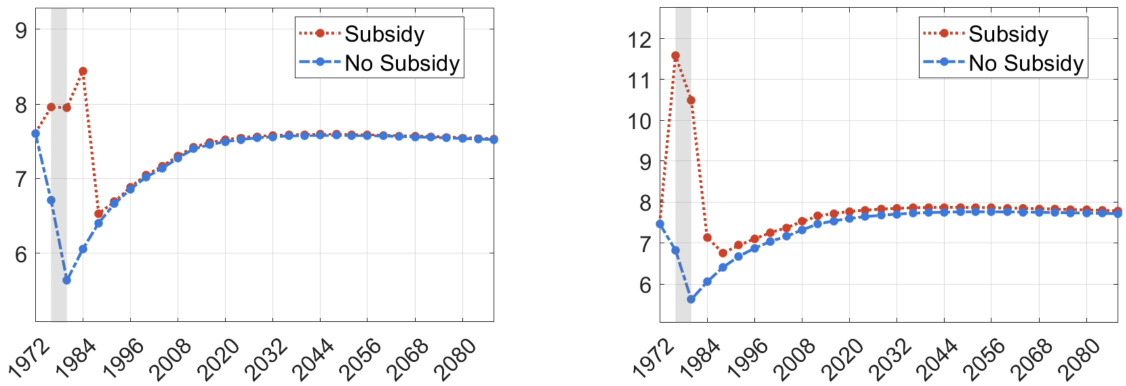
$$\log VA_{it} = \alpha_L \log L_{it} + \alpha_K \log K_{it} + u_{it}, \tag{D.1}$$

where $VA_{it}$ is value added; $L_{it}$ is employment; $K_{it}$ are fixed assets; and $\alpha_L$ and $\alpha_K$ are Cobb-Douglas labor and capital shares.

When using 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 *Annual Reports of Korean Companies*. Therefore, we estimate the production function separately for each sector using the alternative firm-level data. We used *KIS-VALUE* between 1980 and 1990. The *Act on External Audit of Joint-Stock Corporations*, introduced in 1981, requires the Korean firms whose assets were above 3 billion Korean Won were required to report their balance sheet data, which is the source for *KIS-VALUE*. The coverage of our data set is larger than *KIS-VALUE*. Also, because we only 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 between 1970 and 1982.

# Appendix E Appendix: Quantification

## E.1 Additional Figures

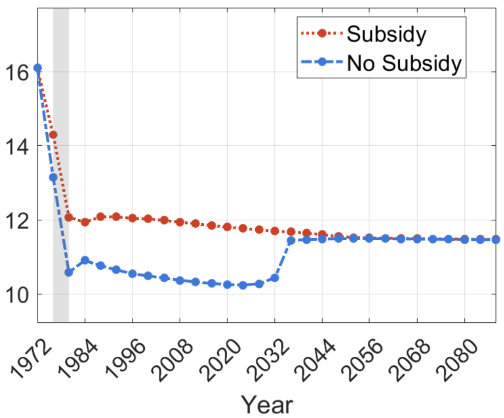



A. Low $\eta$

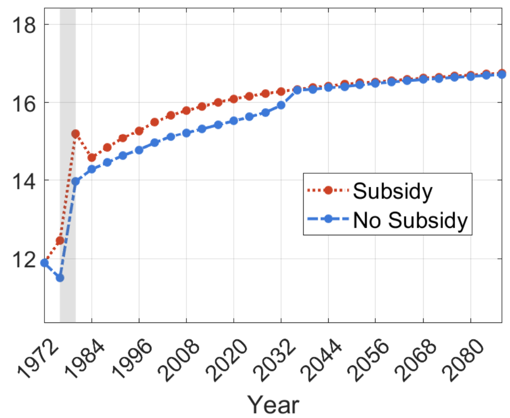
B. Low $\delta$

Figure E1. Heavy Mfg. GDP Shares. Comparative Statistics of $\delta$ and $\eta$

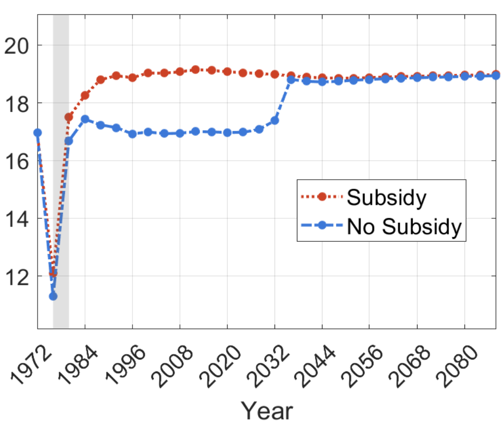
***Notes.*** This figure plots the comparative statistics of $\delta$ and $\eta$. In Panel A, $\eta$ is set 1.05. In Panel B, $\delta$ is set to be 1. The red dotted line and the blue dashed lines plot outcomes of the baseline and counterfactual economies.



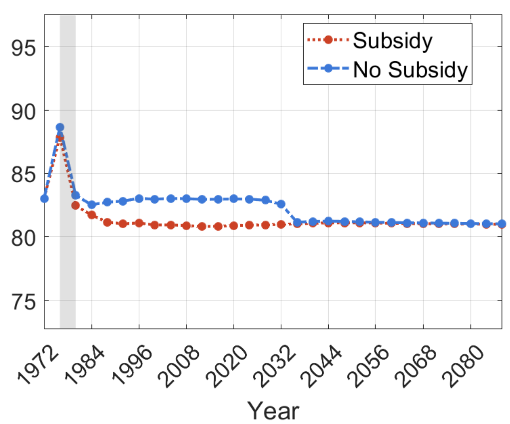

A. Heavy mfg. GDP share (%)




B.Heavy mfg. employment share (%)



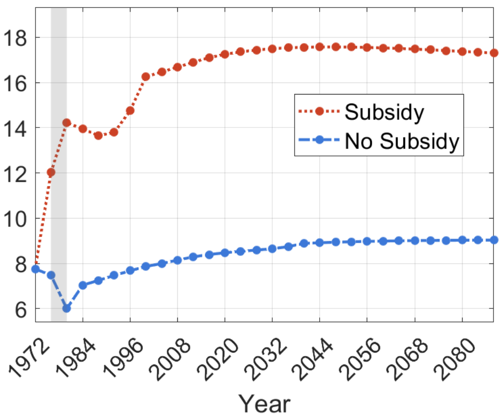

C. Heavy mfg. export share (%)



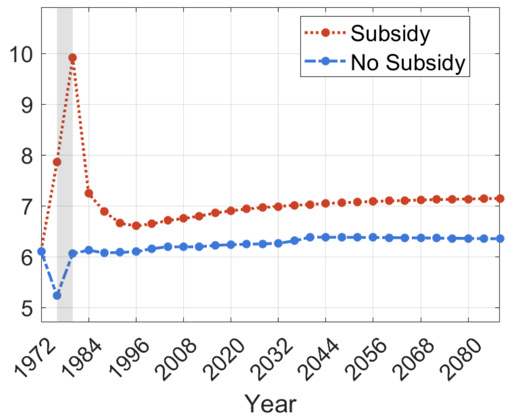

D. Light mfg. export share (%)

Figure E2. The Role of a Roundabout Production Structure and the Temporary Subsidies.

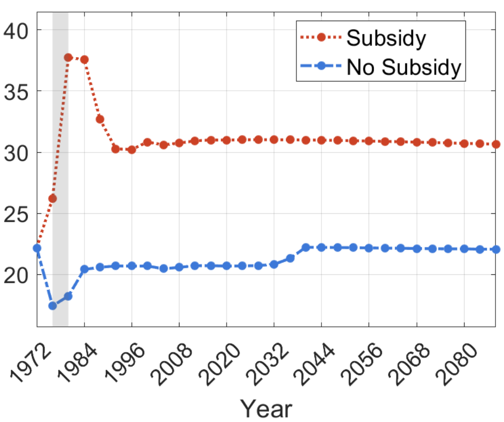
***Notes.*** This figure plots the counterfactual results without a roundabout production structure. Panels A, B, C, and D report the results for the heavy manufacturing sector employment, GDP, and export shares, and the light manufacturing sector export shares, respectively. The red dotted and the blue dashed lines plot outcomes of the baseline and counterfactual economies.



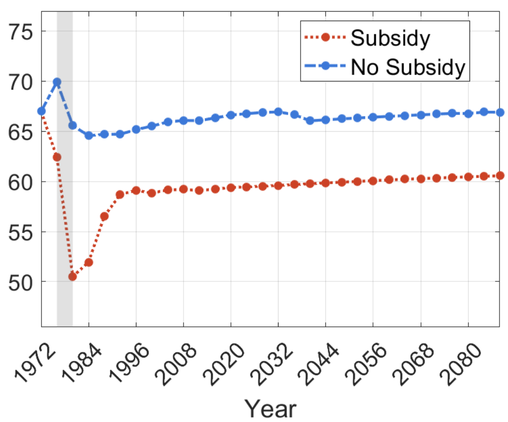

A. Heavy mfg. GDP share (%)




B.Heavy mfg. employment share (%)



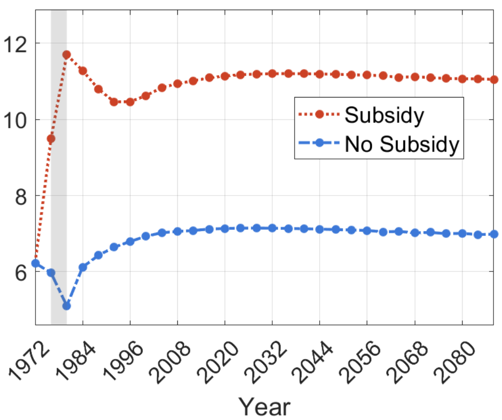

C. Heavy mfg. export share (%)



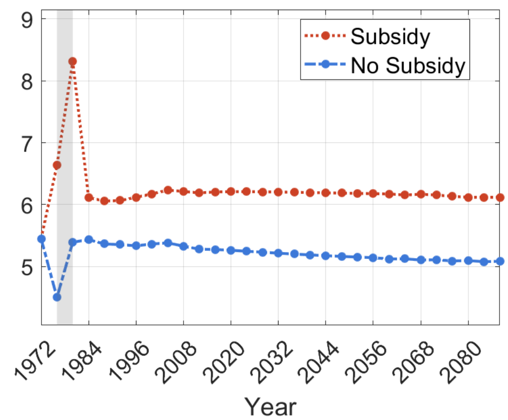

D. Light mfg. export share (%)

Figure E3. The Role of Migration Costs and the Temporary Subsidies.

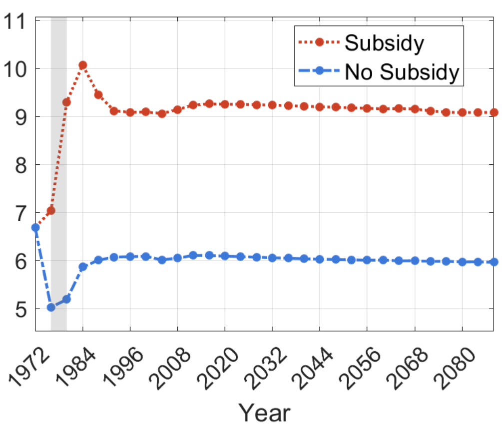
***Notes.*** This figure plots the counterfactual results with a higher level of migration costs than the baseline counterfactual exercises. Panels A, B, C, and D report the results for the heavy manufacturing sector employment, GDP, and export shares, and the light manufacturing sector export shares, respectively. The red dotted and the blue dashed lines plot outcomes of the baseline and counterfactual economies.



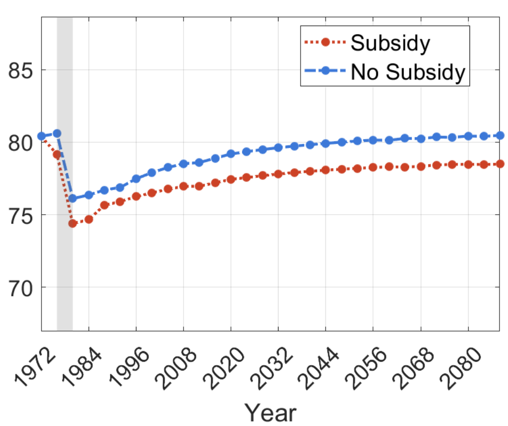

A. Heavy mfg. GDP share (%)




B.Heavy mfg. employment share (%)




C. Heavy mfg. export share (%)




D. Light mfg. export share (%)

Figure E4. The Role of Foreign Market Size and the Temporary Subsidies.

***Notes.*** This figure plots the counterfactual results with a lower level of foreign market size than the baseline counterfactual exercises. 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 and the blue dashed linesplot outcomes of the baseline and counterfactual economies.

## E.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 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 national level
  5. Sectoral import shares at 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 the total expenditure on sector $j$ goods at 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 (6.4))
  2. Median of light & heavy mfg. shares of exports in 1972 across regions
  3. Median of heavy mfg. shares of adopters in 1972 & 1982 across regions
  4. Share of zero adoption regions in 1972 & 1982

**Algorithm.** Taken 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 $\{\phi^{min}_{nj}\}_{n\in\mathcal{N},j\in\mathcal{J}}$
3. Given parameters $\{\mathbf{\Theta}^M, \bar{s}_t\}$, we solve the model and update the fundamentals $\mathbf{\Psi}_t$ for each period. We fit region-sector level aggregate outcomes to the data counterparts. This step corresponds to the constraints of Equation (6.2). 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 $\{D^{f'}_{jt}\}$ using the following equation:

$$\underbrace{\frac{\mathrm{EX}^{Data}_{jt}}{\mathrm{GO}^{Data}_{jt}}}_{\text{Data}} = \underbrace{\frac{\sum_{n\in\mathcal{N}}\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}t^{ex}_{jt}\tau^x_{nj}}{\bar{\phi}^{avg,x}_{njt}}\right)^{1-\sigma} D^{f'}_{jt}}{\sum_{n\in\mathcal{N}}\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}}{\bar{\phi}^{avg}_{njt}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}}\tau_{nmj}P^{\sigma-1}_{mjt}E_{mjt}\right) + \left(\frac{\sigma}{\sigma-1}\frac{c_{njt}t^{ex}_{jt}\tau^x_{nj}}{\bar{\phi}^{avg,x}_{njt}}\right)^{1-\sigma} D^{f'}_{jt}}}_{\text{Model}}$$

(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 $\{V'_{nt}\}$ is identified from the above equation, so we normalize the value of the amenity of the first region to be one for each period, $V'_{1t} = 1, \forall t$.

(d) Update new $\{\phi_{nj}^{min'}\}$ until shares of regional gross output is exactly fitted to the data counterparts:

$$\underbrace{\frac{GO_{njt}^{Data}}{\sum_{m\in\mathcal{N}}\sum_{k\in\mathcal{J}} GO_{mkt}^{Data}}}_{\text{Data}}$$
$$= \underbrace{\frac{\left(\frac{\sigma}{\sigma-1}\frac{c_{njt}}{\bar{\phi}_{njt}^{avg}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}} \tau_{nmj} P_{mjt}^{\sigma-1} E_{mjt}\right) + \left(\frac{\sigma}{\sigma-1}\frac{c_{njt} t_{jt}^{ex} \tau_{nj}^{x}}{\bar{\phi}_{njt}^{avg,x}}\right)^{1-\sigma} D_{jt}^{f'}}{\sum_{n'\in\mathcal{N}}\sum_{k'\in\mathcal{J}} \left(\frac{\sigma}{\sigma-1}\frac{c_{n'k't}}{\bar{\phi}_{n'k't}^{avg}}\right)^{1-\sigma}\left(\sum_{m\in\mathcal{N}} \tau_{n'mk'} P_{mk't}^{\sigma-1} E_{mk't}\right) + \left(\frac{\sigma}{\sigma-1}\frac{c_{n'k't} t_{k't}^{ex} \tau_{n'k'}^{x}}{\bar{\phi}_{n'k't}^{avg,x}}\right)^{1-\sigma} D_{k't}^{f'}}}_{\text{Model}},$$

where

$$\bar{\phi}_{njt}^{avg} = \frac{\theta f(\lambda_{njt-1}^{T})(\phi_{njt}^{min'})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}\left\{\left(\left(\frac{\eta}{1-\bar{s}_{jt}}\right)^{\sigma-1} - 1\right)(\tilde{\lambda}_{njt}^{T})^{\frac{\tilde{\theta}}{\theta}} + \left(1 - \left(\frac{\eta}{1-\bar{s}_{jt}}\right)^{\sigma-1}\kappa^{-\tilde{\theta}}\right)\right\},$$

$$\bar{\phi}_{njt}^{avg,x} = \frac{\theta f(\lambda_{njt-1}^{T})(\phi_{njt}^{min'})^{\sigma-1}}{\tilde{\theta}(1-\kappa^{-\theta})}\frac{(\tilde{\lambda}_{njt}^{x})^{\frac{\tilde{\theta}}{\theta}}}{\lambda_{njt}^{x}}$$
$$\times\left\{\left(\left(\frac{\eta}{1-\bar{s}_{jt}}\right)^{\sigma-1} - 1\right)\left(\frac{\tilde{\lambda}_{njt}^{T}}{\tilde{\lambda}_{njt}^{x}}\right)^{\frac{\tilde{\theta}}{\theta}} + \left(1 - \left(\frac{\eta}{1-\bar{s}_{jt}}\right)^{\sigma-1}\kappa^{-\tilde{\theta}}(\tilde{\lambda}_{njt}^{x})^{-\frac{\tilde{\theta}}{\theta}}\right)\right\},$$

$\tilde{\lambda}^T_{njt} = (1-\kappa^{-\theta})\lambda^T_{njt} + \kappa^{-\theta}$, and $\tilde{\lambda}^x_{njt} = (1-\kappa^{-\theta})\lambda^x_{njt} + \kappa^{-\theta}$. The above equations only identify the relative levels of $\{\phi^{min'}_{njt}\}$, so we normalize the Pareto lower bound parameter of the first region-sector to be 1 for each period, $\phi^{min'}_{11t} = 1, \forall t$.

4. After updating the geographic fundamentals, given values of parameters and subsidies, 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 $\{\hat{\mathbf{\Theta}}^M, \hat{\mathbf{s}}_t\}$ that minimize the objective function in the step 4.

### E.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 2 sectors: light and heavy manufacturing sectors.

#### E.3.1 Aggregate Data

**Initial Shares of Adopters in 1968.** Our firm-level balance sheet data covers between 1970 and 1982, whereas technology adoption contracts cover between 1966 and 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 to their adoption activities and construct shares of adopters in the heavy manufacturing sector for each region.[87]

**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 using the two observed samples. For example, the population share of region $n$ in 1973 is imputed as Pop. $\text{share}_{n,1973} = (\text{Pop. share}_{n,1970})^{\frac{3}{5}} \times (\text{Pop. share}_{n,1975})^{\frac{2}{5}}$. From these imputed values, we obtain population distribution 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.

[87] Given that we cannot observe entry and exit of firms in 1968 and 1969 and we construct the shares based on the firms which survived between 1968 and 1970, this constructed shares are likely to overestimate the actual shares of adopters.

**Region-Sector Level Gross Output in 1972, 1976, and 1980.** We compute gross output at region-sector level by harmonizing firm-level data and the input-output table. Using the firm-level data, we calculate a share of sales of firms in region $n$ and sector $j$ and then multiply this share with 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-level input-output tables. Aggregate export share is calculated 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 is zero. Aggregate sectoral import share is calculated as $IM_{jt}^{Data}/E_{jt}^{Data}$, where $IM_{jt}^{Data}$ and $E_{jt}^{Data}$ is sector $j$'s imports and expenditure. 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.** Export and import tariffs data are not used for the reduced-form empirical analysis but only for the quantitative exercises. The export tariffs data are obtained from Magee (1986).[88] The original data set's industry code is in 4-digit 1972 SIC code. It is first converted into 4-digit 1987 SIC codes and then converted into ISIC Revision 3 codes.[89]

Import tariff data are digitized from Luedde-Neurath (1986) for 1974, 1976, 1978, 1980, and 1982, which are in the Customs Cooperation Council Nomenclature (CCCN). CCCN is converted into ISIC Revision 3, and then it is averaged across 4-digit ISIC codes. For missing years, we impute values using the geometric average. We assume that the tariff level in 1972 is the same as that in 1974.

We aggregate trade tariffs up to the 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 actual magnitude of the tariffs. However, the quantitative results are not affected regardless of weighting or not.

[88] The US export tariff data was downloaded from https://cid.econ.ucdavis.edu/ust.html.

[89] The concordance between 1972 SIC and 1987 SIC is obtained from "www.nber.com."

### E.3.2 Micro moments

We can compute shares of adopters for each year using our data set. After computing these shares across regions and years, we compute the median for 1972 and 1980. Also, using this information, we can compute shares of regions with zero values. Shares of exporters are similarly obtained. However, because of many missing samples on exports, we take the three-year moving averages on shares of exports for each region-sector. We count firms with missing information on exports as non-exporters. Section E.4 describes calculating the identifying moment in more detail.

## E.4 Identifying Moment for Subsidy

**Calibration Procedure.** Using data on shares of adopters of the heavy manufacturing sector across regions in 1972 and 1980, we run the following regression model via PPML:

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

where $D^{policy}_t$ is a dummy variable which equals one in 1980; and $\lambda^T_{n,heavy,t}$ is a heavy manufacturing share of adopters of region $n$ in period $t$. One period of the model corresponds to 4 years in the data, so $\lambda^T_{n,heavy,t-1}$ is lagged by 4 years. Standard errors are clustered at regional level. The estimated coefficients are reported in Table E1.

Table E1: Identifying Moment for Subsidy

| 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.*** The table reports the OLS estimates of Equation (E.1). Standard errors are clustered at region level and are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Using model-generated data, we run the same regression model. Following Silva and Tenreyro (2006), we calculate the estimate of $\beta^{policy}$ by solving the first order condition of log-likelihood of PPML:

$$\sum_{n \in \mathcal{N}} \mathbf{X}_{nt}(\lambda^T_{n,heavy,t} - exp(\mathbf{X}'_{nt}\boldsymbol{\beta})), \tag{E.2}$$

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 2.** Note that the assumptions of Proposition 2 are not satisfied in both data and model, and we run the regression only for the heavy manufacturing sector. However, we show that $\hat{\beta}^{policy}$ is still informative on $\bar{s}$.

Under the unbounded Pareto distributional assumption, we can derive the following relationship from the model for the heavy manufacturing sector without any additional assumptions:

$$
\begin{aligned}
&\ln \lambda^T_{n,heavy,t} - \theta\delta\lambda^T_{n,heavy,t-1} \\
&\quad = \underbrace{\frac{\theta}{\sigma-1}\ln\left(\left(\frac{\eta}{1-s_{n,heavy,t}}\right)^{\sigma-1} - 1\right) \underbrace{-\theta\ln\left(\frac{\mu c_{n,heavy,t}(\sigma c_{n,heavy,t} F^T_{heavy})^{\frac{1}{\sigma-1}}}{\left(\sum_{m\in\mathcal{N}} P^{\sigma-1}_{heavy,t} E_{m,heavy,t} + D^f_{heavy,t}\right)^{\frac{1}{\sigma-1}}}\right)}_{=\mathbf{GE}_{n,heavy,t}(\mathbf{\Psi}_t,\mathbf{s}_t)}}_{=D^{policy}_t} \\
&\qquad + \underbrace{\theta\ln\phi^{min}_{n,heavy,t}}_{=\epsilon_{n,heavy,t}}.
\end{aligned}
$$

Because the heavy manufacturing sector is the only sector where technology adoption is available and targeted by the government, $D^{policy}_t$ are not separately identified from additional time fixed effects.

$D^{policy}_t$ captures both the subsidies in the second term of the RHS, and the general equilibrium effects in the third term of the RHS. $\mathbf{GE}_{n,heavy,t}(\mathbf{\Psi}_t, \mathbf{s}_t)$ which depend all other regions' geographic fundamentals $\mathbf{\Psi}_t$ and subsidies $\mathbf{s}_t$. $\mathbf{GE}_{n,heavy,t}(\mathbf{\Psi}_t, \mathbf{s}_t)$ is a function of own exogenous natural advantage in the error term and therefore is correlated with the error term, which leads to the endogeneity problem of the above regression model. In Proposition 2, by imposing the additional assumptions, these general equilibrium effects could be absorbed out by region fixed effects, which is not the case in the above regression model.

However, although $\hat{\beta}^{policy}$ is biased, it is still informative on $\bar{s}$. For given values of $\bar{s}$ and other structural parameters, we back out geographic fundamentals by exactly fitting region-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 as fitting the joint effects of both the subsidies in the second term and $\mathbf{GE}_{n,heavy,t}(\mathbf{\Psi}_t, \mathbf{s}_t)$.

### E.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 data set among the accessible population census data. Because of the data availability, regions are aggregated up to 35 regions. $\mu^{1995}_{nm1990}$ is obtained as the total number of migrants moving from region $n$ to region $m$ between 1990 and 1995 divided by the total population of region $n$ in 1990. When computing the total population and migrants, we restrict our sample age between 20 and 55. We also exclude both 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 $\epsilon^d_{mnt}$ that is orthogonal to distance between two regions: $d_{mn} = (dist_{mn})^{-\zeta}\epsilon^d_{mnt}$. Taking log of Equation (5.10), we can derive the following regression model:

$$\begin{aligned}\ln \mu^{1995}_{mn1990} = -\nu\zeta \log dist_{mn} + \underbrace{\ln\left(V_{n,1995}\frac{(1-\bar{\tau}^w_{1995}+\bar{\pi}^h_{1995})w_{nt}}{P_{n,1995}}\right)}_{=\delta_n} \\ + \underbrace{\ln\left(\sum_{n'=1}^{N}\left(V_{n',1995}\frac{(1-\tau^w_{1995}+\bar{\pi}^h_{1995})w_{n',1995}}{P_{n'1995}}d_{mn'}\right)^{\nu}\right)}_{\delta_m} + \epsilon^d_{mnt},\end{aligned}$$

which gives Equation (6.1). We estimate the above equation using OLS and PPML. The results are reported in Table E2. The estimated coefficient is around -1.30. The magnitude of the estimate implies that one percent increase in distance decreases outward migration share by 1.3%.

Table E2: Gravity Equation of Migration Shares

| Dep. Var. | Migration Shares between 1990 and 1995 | |
|---|---|---|
| | OLS | PPML |
| | (1) | (2) |
| $\log Dist_{mn}$ | –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.*** The table reports the gravity estimates of Equation (6.1). Dependent variable is log of migration share from region $m$ to region $n$ between 1990 and 1995. In column (1), we estimate the model using OLS. In column (2), we estimate the model using the Poisson pseudo likelihood estimation (Silva and Tenreyro, 2006). Clustered errors are two-way clustered at origin and destination levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.