Technology Adoption and Late Industrialization*

Jaedo Choi
Federal Reserve Board

Younghun Shim
University of Chicago

August, 2023

Abstract

We study the role of foreign technology adoption in driving late industrialization in developing countries. Leveraging unique historical data from South Korea, we provide three empirical findings on firm-level effects of technology adoption: direct effects on adopters, local spillovers, and local complementarity in adoption. We develop a dynamic spatial general equilibrium model consistent with these findings. Due to the complementarity, the model has the potential for multiple steady states. Using this model, we evaluate the South Korean government policy that provided temporary adoption subsidies to heavy manufacturing firms. Our results suggest that such a big push policy could have yielded permanent effects by shifting the economy towards a more industrialized steady state, characterized by higher heavy manufacturing sector's GDP shares and increased adoption levels.

Keywords: technology adoption, industrialization, complementarity, big push, knowledge diffusion

JEL Codes: O14, O33, O53, R12

*The views expressed in this paper are our own, and do not represent the views of the Board of Governors of the Federal Reserve, nor any other person associated with the Federal Reserve System. We are grateful to Andrei Levchenko, Dominick Bartelme, Jagadeesh Sivadasan, and Sebastian Sotelo for their guidance and invaluable suggestions. We thank David Argente, Costas Arkolakis, Maria Aristizabal-Ramírez, David Atkin, Natalie Bau, Barthélémy Bonadio, Yongsung Chang, Victor Couture, Javier Cravino, Dave Donaldson, Elisa Giannone (discussant), Kyle Handley, Ricardo Hausmann, Oleg Itskhoki, Joe Kaboski, Yongjun Kim, Sam Kortum, Mos Laoprapassorn, Kevin Lim, Kiminori Matsuyama, Isabelle Mejean (discussant), Peter Morrow, Nathan Nunn, Nishaad Rao, Ulrich Schetter, Yongseok Shin, Michael Song, Dan Trefler, Nick Tsivanidis, Jon Vogel, Kei-Mu Yi, Xiaodong Zhu for helpful comments and discussions. We also thanks participants at the IGC-Stanford Conference on Firms, Trade, and Development, USC/UNIL/Bank-al-Maghrib Workshop, 2023 SED, 2023 STEG Annual Conference, 2022 STEG Theme 0 Workshop, 2022 ETSG, 2022 EWMES, 2022 MWIT, and seminar participants at Berkeley Haas, CUHK, Federal Reserve Board, Harvard Growth Lab, HKU, HKUST, JHU-SAIS, KDI, KIEP, KIF, KIPF, LSE, Maastricht, Michigan, NTU, PSU (New Faces in International Economics), Rochester, SNU, Toronto, UBC, UCLA, VEAMS, Yale, and Yonsei for comments. We gratefully acknowledge research support from the Kwanjeong Educational Foundation. E-mail: jaedo.choi@frb.gov.

1 Introduction

In the postwar period, patterns of industrialization among developing countries diverged. The economic base of some latecomers such as South Korea, Taiwan, and Turkey transformed from agriculture to manufacturing, while many others remained stagnant. These latecomers achieved industrialization by adopting foreign technology rather than developing their own technology, known as late industrialization (Amsden, 1989).[1] Although late industrialization among these latecomers provides suggestive evidence about the importance of technology adoption for economic development (e.g. Parente and Prescott, 2002), little is empirically or quantitatively known about the role of technology adoption during their industrialization due to the unavailability of detailed data.

This paper studies the contribution of foreign technology adoption to late industrialization. The focus of our study is South Korea in the 1970s, which presents an intriguing setting for two key reasons. First, South Korea experienced a remarkable economic transformation, earning recognition for its growth miracle (Lucas, 1993). Second, during this period, the Korean government implemented a policy that temporarily subsidized technology adoption. This policy has prompted discussions regarding the role of a big push in fostering its economic development (Murphy et al., 1989) Thus, our setting provides a valuable opportunity to explore the effects of such a policy on technology adoption.

This paper makes three contributions related to technology adoption: measurement, empirical analysis, and quantification. First, to directly measure firm-level adoption activities, we construct a novel historical dataset that covers the universe of technology adoption by South Korean firms. Second, we provide three novel empirical pieces of evidence on firm-level effects of technology adoption: direct effects on adopters, local spillovers, and local complementarity in firms' adoption decisions. Third, we develop a quantitative model consistent with these empirical findings and use it to evaluate the big push policy implemented by the Korean government.

Our dataset includes all technology adoption contracts between South Korean and foreign firms. By analyzing this comprehensive dataset, we can derive aggregate implications from micro-level findings. The dataset was constructed by collecting and digitizing adoption-related contract documents that firms were required to report to government authorities. Most of the adopted technologies were related to knowledge about building and operating plants and capital equipment for mass production. The data reveal a novel pattern: while the heavy manufacturing sector's share of South Korea's GDP increased from 6% to 14%, there was a significant influx of new technologies through adoption contracts, with the number of new contracts of heavy manufacturing sectors quadrupling over the sample period.

Using this constructed dataset, we provide three empirical pieces of evidence on the firm-level

[1] 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. "If industrialization first occurred in England on the basis of invention, and if it occurred in Germany and the US on the basis of innovation, then it occurs now among "backward" countries on the basis of learning" (Amsden, 1989, p. 4).

effects of technology adoption. These three findings uncover how technology adoption affected firm performance in the late-industrializing economy. Our first finding is the direct effects on adopters. We address the empirical challenge of selection bias by employing a winners vs. losers research design (Greenstone et al., 2010). We compare firms that successfully adopted technology (winners) and firms that received the approval from the government to pursue foreign technology and made a contract with a foreign firm but *failed* to or *got delayed* to adopt technology because the foreign firm canceled the contract due to circumstances seemingly unrelated to the South Korean firm (losers). We construct matches of winners and losers by matching each loser to winners that are observationally similar. Using these matches, we adopt the stacked-by-event design (Deshpande and Li, 2019; Cengiz et al., 2019) in which the treatment effects are estimated only based on comparisons between winners and never-treated or not-yet-treated losers. We find technology adoption increased winners' sales and revenue-based total factor productivity (TFP) by around 92% and 64%, respectively.

Our second finding is local spillovers of technology adoption. We regress growth in sales or revenue-based TFP on changes in local region-sector level adopter shares, controlling for fixed effects and other controls. To identify the spillovers, we propose an instrumental variable (IV) strategy based on business groups' spatial networks of affiliated firms across region-sectors (Moretti, 2021). We use variation in changes in the adoption status of firms outside of a region that are affiliated with business groups that own at least one firm in that local region. Our estimates reveal semi-elasticities of sales and revenue-based TFP with respect to local shares of approximately 4% and 1.2%, respectively.

The third finding is local complementarity in firms' adoption decisions, that is, a higher share of adopters leads to more adoption. We regress a dummy variable of making a new adoption contract on local region-sector level adopter shares using the same IV strategy. We find that increases in local adopter shares lead to higher probabilities of making new contracts.

Motivated by these three empirical findings, we develop a simple model that incorporates firms' technology adoption decisions and spillovers from such adoption. Firms can adopt a more productive modern technology after incurring a fixed adoption cost in units of final goods. Spillovers operate with a one-period lag, where current productivity increases in the adopter shares from the previous period. This lag introduces dynamics to the model, with the share of adopters becoming a time-varying state variable. The model features dynamic complementarity in firms' adoption decisions, that is, a higher share of adopters in the previous period leads to a higher share in the current period. The complementarity arises due to the lower fixed adoption costs resulting from lagged spillovers.

The model rationalizes the possibility of the big push. We demonstrate analytically that dynamic complementarity can lead to multiple steady states: pre-industrialized and industrialized steady states with low and high adopter shares. The long-run outcome depends on the initial conditions, indicating path dependence, where temporary events can permanently shape long-run outcomes (Nunn, 2014; Voth, 2021). The big push policy, which provides a one-time subsidy for adoption, can have permanent effects by moving the economy away from initial conditions that would lead to the pre-industrialized state.

To conduct a counterfactual analysis of the policy, we extend the model to incorporate internal and international trade, input-output (IO) linkages, and migration. We calibrate the model using micro and regional data, ensuring a tight connection between the model and the data. The model's structural equations align with our reduced-form regression specifications, allowing us to estimate key parameters governing the direct productivity gains and spillover effects.

Using the calibrated model, we evaluate how the pattern of industrialization in South Korea would have evolved differently without the big push policy. Our results show that in the absence of the policy, South Korea would have converged to an alternative less-industrialized steady state. In this scenario, the heavy manufacturing sector's share of GDP would have been 3.1 percentage points lower, and its export share to total exports would have been 27.1 percentage points lower compared to the steady state of the baseline economy with the policy.

Related literature Our paper contributes to three strands of the literature. First, it adds to the empirical literature that investigates firm-level effects of industrial technology adoption in developing countries (e.g., Atkin et al., 2017; Juhász, 2018; Juhász et al., 2020; de Souza, 2021; Giorcelli and Li, 2021; Hardy and McCasland, 2021). We provide novel empirical findings on the firm-level effects of technology adoption during South Korea's late industrialization. Our spillover findings align with previous studies on spillover effects of foreign direct investment and new technologies (e.g., Keller, 2002; Javorcik, 2004; Giorcelli, 2019; Bai et al., 2020; Alfaro-Ureña et al., 2022; Bianchi and Giorcelli, 2022). However, unlike these studies, we provide new evidence on local complementarity in firms' technology adoption decisions.

Second, our paper relates to the literature on multiple equilibria and the big push, which examines underdevelopment caused by coordination failures (e.g., Rosenstein-Rodan, 1943; Hirschman, 1958; Murphy et al., 1989; Matsuyama, 1991, 1995; Redding, 1996; Rodríguez-Clare, 1996; Ciccone, 2002; Diodato et al., 2022; Alvarez et al., 2023). While previous studies have theoretically explored the concept of the big push, its quantitative dimensions remain less understood. Our contribution lies in quantitatively exploring the possibility of the big push and evaluating the actual policy. Notably, three recent papers are closely related to our study (Kline and Moretti, 2014; Buera et al., 2021; Alvarez et al., 2023). Kline and Moretti (2014) document limited evidence of the big push through the Tennessee Valley Authority program in the United States. Our model, similar to theirs, generates multiple equilibria due to path dependence induced by local spillovers. However, we find that the big push can explain the late industrialization of South Korea. In contrast to Buera et al. (2021) who study complementarity in technology adoption decisions and its interaction with distortions, our model highlights the role of local spillovers in generating complementarity. Additonally, Alvarez et al. (2023) study a dynamic model of adoption of peer-to-peer payment instruments featuring strategic complementarities, whereas our study focuses on industrial technologies and incorporates rich spatial heterogeneity.

Third, this paper relates to the literature on South Korea's growth miracle (e.g., Westphal, 1990; Young, 1995; Lee, 1996; Ventura, 1997; Connolly and Yi, 2015; Itskhoki and Moll, 2019). We study the role of technology adoption in South Korea's industrialization. Two closely related papers are Lane (2022) and Choi and Levchenko (2023). Unlike these papers, which analyze the long-term effects of subsidies provided by South Korea's industrial policy at the sector- or firm-level, our empirical analysis focuses on the firm-level effects of technology adoption, with subsidies being a potential source of endogeneity concern in our analysis. Furthermore, our quantitative analysis concentrates on the specific channel of the policy through technology adoption and demonstrates that the big push can be a potential explanation for the long-run effects of the policy documented in Lane (2022) and Choi and Levchenko (2023). In line with Rodrik (1995), this paper focuses on how South Korea *got its interventions right* by promoting technology adoption. Another closely related paper is Choi and Shim (2022) who examine the role of technology adoption and innovation in South Korea's catching-up growth, focusing on the post-1980s period. In contrast, this paper explores the role of technology adoption in industrialization and sectoral industrial policy in the 1970s.

Structure The remainder of this paper is structured as follows. Section 2 provides an overview of the data used in this study and outlines the historical background of South Korea's late industrialization. In Section 3, we present three empirical findings that explore the firm-level effects of technology adoption. Section 4 introduces a simple model that is consistent with these empirical findings and provides an analytical characterization of the potential multiple equilibria and the possibility of the big push. Section 5 describes the full quantitative model and the calibration procedure. Section 6 presents the counterfactual results on the big push policy. Section 7 concludes.

2 Data and Historical Background

2.1 Data

We construct our main dataset by merging firm-level balance sheet data with information on firms' technology adoption activities based on firms' names. We classify these firms into 10 manufacturing sectors, of which 4 are categorized as heavy manufacturing. The sample period covers the years 1970 to 1982. Further details regarding the data construction process can be found in Section A.

Technology adoption We hand-collected and digitized firm-level data on technology adoption from official documents related to domestic firms' technology contracts with foreign firms from the National Archives of Korea and from the Korea Industrial Technology Association (1988).[2] These documents provide information about the names of domestic and foreign contractors, as well as the

[2] Any domestic firms' transactions with foreign firms, including technology adoption contracts, were strictly regulated under the Foreign Capital Inducement Act, first enacted in 1962. 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 in the economic policy-making process in South Korea during the sample period. Beginning in 1961 and continuing until the mid-80s, the EPB met every month and discussed new technology contracts. The National Archives of Korea collected and preserved the documents the EPB examined in its monthly meetings.

calendar years in which the contracts were made, spanning the period from 1962 to 1988. The dataset includes 1,698 contracts made by 628 unique firms, with 1,361 contracts and 457 firms in the heavy manufacturing sectors. Approximately 95% of the contracts involved the transfer of know-how, such as transfers of blueprints or training service[3]

Balance sheet and geographic information Firm balance sheet data is obtained by digitizing the Annual Reports of Korean Companies, which are published by the Korea Productivity Center. These reports cover firms with more than 50 employees and provide information on sales, assets, fixed assets, and establishment addresses for the sample period spanning from 1970 to 1982 (with employment data available starting from 1972). By utilizing the addresses of firms' plants, we link their adoption activities to their respective production locations. The firm balance sheet information in our dataset is representative at the national level and includes a total of 7,223 unique firms, of which 49% are classified as heavy manufacturing. On average, the dataset covers 67% of sectoral gross output based on IO tables obtained from the Bank of Korea.

Adoption subsidy Subsidies constitute a significant source of endogeneity concern for our empirical analysis. To address this, we acquire firm-level subsidy data from Choi and Levchenko (2023), who have compiled information on foreign credit allocation by the government. We employ this data as controls and to test the identifying assumptions in our empirical analysis. One of the primary subsidy instruments utilized by the government was the allocation of foreign credit (Amsden, 1989; Rodrik, 1995). The government selectively granted access to foreign credit to targeted firms and provided guarantees for this credit once it was granted.[4] As a result of the government guarantee, targeted firms could borrow at significantly lower interest rates than those available from domestic sources. A substantial portion of this credit was allocated to subsidize heavy manufacturing firms' acquisitions of costly capital equipment associated with newly adopted technologies (Enos and Park (1988)). However, while we possess information on the total amount of credit allocated to each firm, we do not observe the specific amount allocated to individual adoption contracts.

Sectoral and regional data We obtain South Korea's import tariffs from Luedde-Neurath (1986). Additionally, IO tables are sourced from the Bank of Korea. Regional population data is obtained from the Population and Housing Census.

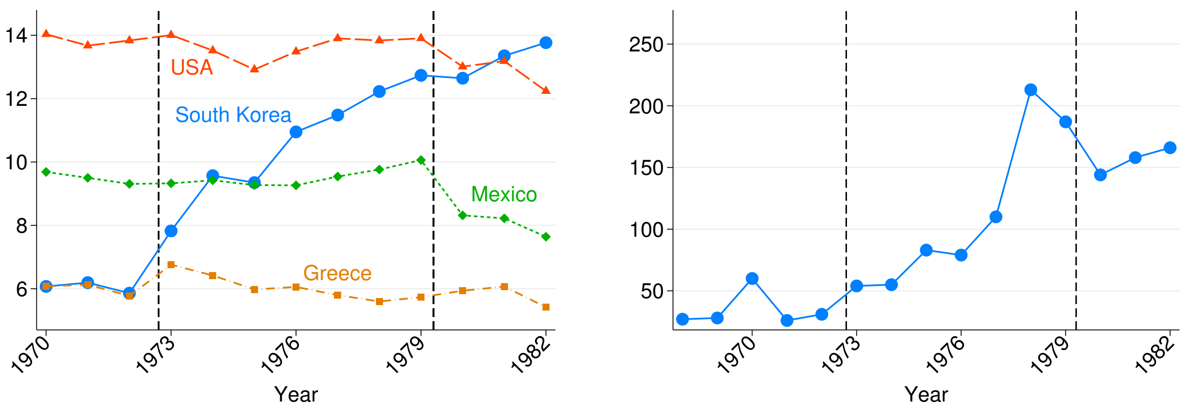
2.2 Late Industrialization in South Korea

In the late 1972, the Korean government launched the Heavy and Chemical Industry (HCI) Drive to modernize and promote heavy manufacturing sectors, including chemicals, electronics, machinery,

[3]For example, Figure A1 is one page of the contract document between Kolon (South Korean) and Mitsui Toatsu (Japanese), both of which are chemical manufacturers. The contract shows that Mitsui had to provide blueprints, send skilled engineers to train South Korean workers, and provide training service by inviting South Korean engineers to its plants in Japan.

[4]Due to restrictions imposed by the 1962 Foreign Capital Inducement Act to control the balance of payments, direct financial transactions between domestic firms and foreign firms were regulated (Choi and Levchenko (2023)).

Figure 1. Late Industrialization and Technology Adoption in South Korea



A. Heavy mfg. share of GDP (%)

B. # of new adoption contracts made by heavy mfg. firms

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 the heavy manufacturing sector's share of GDP across countries from the OECD STAN Structural Analysis Database and the OECD National Accounts Statistics database.

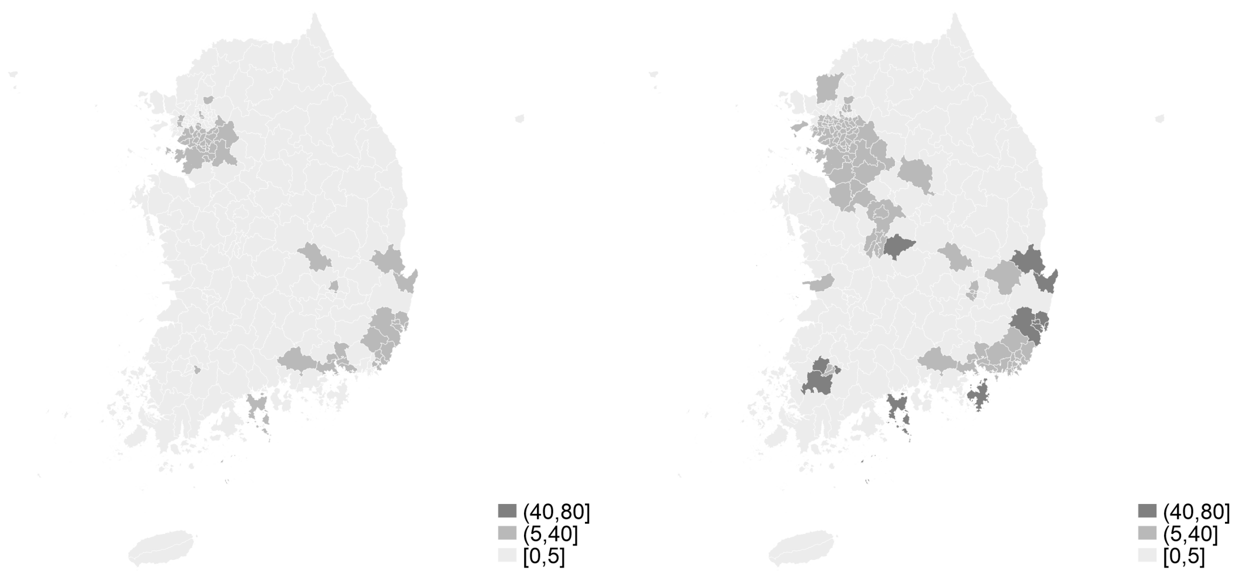
steel, non-ferrous metal, and transport equipment. The timing of the policy and selection of the targeted sectors were driven by a political shock rather than economic conditions due to the Nixon Doctrine (1969) and the military tension with North Korea (Lane, 2022).[5] The heavy manufacturing sectors, which were related to the arms industry, were targeted for the modernization of South Korea's military forces and achieving self-reliant defense. The HCI Drive was a temporary policy that ended in 1979 after President Park was assassinated.

When promoting the heavy manufacturing sectors, the government heavily subsidized the adoption of foreign industrial technology. The government considered South Korea's underdeveloped technology in heavy manufacturing sectors as one of the national threats, and given its large technology gap with the world frontier, the government deemed technology adoption to be the most effective way to catch up with the frontier (Ministry of Science and Technology, 1972).[6] Technology adoption

[5] After the Vietnam War, in the Nixon Doctrine (1969), President Nixon demanded more responsibility from its East Asian allies for their self-defense instead of relying on the US military. The doctrine posed a threat to South Korea's national defense due to rising military tension with North Korea and its heavy reliance on the US military.

[6] "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 the competitiveness of our exported goods in international markets and national power, which bodes ill for our chance of a peaceful reunification with North Korea. . . . 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. 3–4)

Figure 2. Geographic Concentration of Technology Adoption Activity



Local heavy mfg. adopter shares (%)

A. 1972 B. 1979

Notes. The figure illustrates the heavy manufacturing adopter shares in each region in 1972 and 1979. The cutoffs of 40% and 70% correspond to the 99th percentile of the distribution of the 1972 shares and the maximum of the 1979 shares.

was the main means of technology transfer from foreign developed economies to South Korea.[7]

While at the beginning of our analysis period South Korea's GDP share of the heavy manufacturing sector was only 6%, it achieved a remarkable takeoff during the sample period, surpassing Mexico by the mid-70s and the US by 1982 (Panel A of Figure 1).[8] Our data reveals that this industrialization in heavy manufacturing sectors was accompanied by inflows of new foreign technologies, with the yearly number of contracts quadrupling during the same period (Panel B). Consistent with the policy narrative, this sudden increase in technology adoption coincided with the government policy from 1973 to 1979. Even after the policy ended, the economy continued to specialize in the heavy manufacturing sectors.

The narrative of the one-time policy and the rapid pattern of industrialization have led to conjectures about the big push behind South Korea's economic development. Later, we show that the local spillovers and complementarity can rationalize the possibility of the big push. In fact, these local

[7]Another commonly used means of technology transfer in developing countries is foreign direct investment (FDI). However, in South Korea, FDI did not play a significant role due to government regulations on FDI (Kim, 1997, p.42-43).

[8]Consistent with the GDP shares, employment and export shares of the heavy manufacturing sectors also increased from 4 to 8% and from 13.7 to 35% between 1970 and 1982.

effects are consistent with a spatially uneven rise in adoption activities, which were concentrated in the Northwestern and Southeastern regions (Figure 2).

3 Empirical Evidence on Firm-Level Effects of Technology Adoption

In this section, we present three empirical findings on firm-level effects of technology adoption in the late industrializing economy: direct effects on adopters, local spillovers, and local complementarity in firms' adoption decisions.[9]

3.1 Direct Effects on Adopters

Winners vs. losers research design When estimating the direct effects on adopters, one of the key econometric challenges is that firms make adoption decisions endogenously. Unobservable systematic differences between adopters and non-adopters may result in a spurious correlation between adoption status and adopters' performance, resulting in a selection bias problem. To overcome this challenge, we implement a winners vs. losers research design, drawing on Greenstone et al. (2010), which generates quasi-experimental variation in both adoption status and timing. By comparing firms that successfully adopted technology (winners) with firms that had contracts approved but *failed to adopt* or *got delayed to adopt* due to external factors (losers), we can control for underlying unobservable factors that made firms self-select into adoption.

We define winners (the treated) as firms that successfully adopted technology from foreign firms. We define losers (the comparison) as firms that made contracts with foreign firms that got approved by the government but were not able to adopt or got delayed to adopt foreign technology because the foreign firm canceled the contract for reasons that are external to the South Korean firm. Examples include cancellations due to foreign firms' bankruptcy, changes in management team of foreign firms, or foreign firms' sudden requests to change contractual clauses after making a deal. We exclude cancellations by domestic firms, such as domestic firms' sudden decreases in cash flow. 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 cancellations by reading these documents from the archive.

Among these losers, there are two types of losers, delayed- and never-adopters. The delayed-adopters are firms that eventually adopted foreign technology but the timing of the adoption got delayed due to the cancellation. The never-adopters are firms that never adopted technology after the cancellation. Therefore, the cancellations generate exogenous variation in adoption timing for some losers or status for the others.

Each loser is matched with up to three winners who made contracts in the same year as the loser's

[9] Related to these three findings, we give an example of POSCO, the first integrated steel mill in South Korea and now one of the top five steel producers globally. POSCO's successful adoption of foreign technology, the subsequent knowledge diffusion to smaller local firms through labor mobility (Enos and Park, 1988, pp.210-211), and the facilitation of further adoption due to the availability of cheaper domestic capital inputs relate to these three findings (POSCO, 2018, pp.138-141). See Appendix B.1 for more details.

contract that was eventually canceled. Matching proceeds in two steps. First, we exactly match on region-sectors to absorb shocks common within region-sectors, such as market size or local labor market conditions. Second, within region-sectors, we pick winners that were most similar to a loser in terms of firm size or growth measured by log assets, log fixed assets, and one-year growth rates of these two variables, where the similarity is measured by the Mahalanobis distance. The matching allows for replacements, enabling one winner to be matched with multiple losers. When there are more than three available winners, the most similar three are selected, and if there are fewer than three available winners, all winners are kept. The matching procedure results in 35 matches among 91 unique firms, with 23 not-yet-treated losers and 12 never-treated losers.

Using the matched winners and losers, we estimate the following event study specification:

$$y_{imt} = \sum_{\tau=-4}^{7} \beta_\tau (D_{mt}^\tau \times \mathbb{1}[\text{Winner}_{it}]) + \delta_{im} + \delta_{mt} + \epsilon_{imt}, \tag{3.1}$$

where i denotes firm, m match, and t year. y_{imt} is a firm outcome. D_{mt}^τ are event-study dummies defined as $D_{mt}^\tau := \mathbb{1}[t-\tau = t(m)]$, where $t(m)$ is the event year of match m. $\mathbb{1}[\text{Winner}_{it}]$ is a dummy variable of winners. We normalize β_{-1} to one. δ_{im} and δ_{mt} are match-firm and match-year fixed effects. ϵ_{imt} is an error term. Matching with replacement introduces mechanical correlation across residuals, because of the possible appearance of the same firm. Thus, we cluster standard errors at the firm level.

One issue with estimating Equation (3.1) is staggered rollout design that leverages comparison between already-treated adopters and delayed-losers, which induces a bias under the presence of heterogeneous treatment effects across cohorts (e.g., Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2023). To deal with this issue, we adopt a stacked-by-event design (Cengiz et al., 2019; Deshpande and Li, 2019) and construct our estimation dataset based on rolling control groups as follows. Within each match, we drop matches when delayed-losers adopt technology in later periods. By doing so, we limit attention to comparisons between treated winners and not-yet-treated or never-treated losers, avoiding the forbidden comparison problem.

Identifying assumption Our identifying assumption is that losers serve as valid counterfactuals for winners. We require that losers and winners should be ex-ante similar in terms of both observables and unobservables prior to the event conditional on matched controls and fixed effects, and cancellations should be uncorrelated with domestic firms' unobservables. Raw data plots support this assumption, as the average log sales of winners increased only after cancellations, while the average of losers followed a similar trend to their pre-trends (Panel A of Appendix Figure B1). Also, despite the small number of losers, the distribution of cancellations by sectors closely resembles that of total contracts, supporting that cancellations were random events (Panel B of Appendix Figure B1).

To further test this identifying assumption, we conduct three exercises. First, we assess covariate balance by comparing levels of outcomes between winners and losers before the cancellations and find that both groups are well-balanced. Also, we compare patenting activities between groups of foreign firms that made contracts with winners and losers, using the US patent data obtained from US Patent and Trademark Office (USPTO), where patenting activities are interpreted as indicators of performance of foreign firms. We find that various measures of patent activities are similar between the two groups, ruling out the possibility of matching losers with less competent foreign firms (Appendix Table B1). Second, we regress pre-event observables on a dummy of losers. We find that these observables do not predict cancellations regardless of whether they are controlled individually or jointly (Appendix Table B2). Third, and most importantly, to check the parallel trend assumptions, we inspect pre-trends before the cancellations.

Comparison with the full-sample TWFE estimator To assess the implications of correcting for the endogeneity issue, we compare the baseline estimates to those obtained from a two-way fixed effect (TWFE) event study specification using the full sample:

$$y_{it} = \sum_{\tau=-4}^{7} \beta_\tau (D_{it}^\tau \times \mathbb{1}[\text{Adopt}_{it}]) + \delta_i + \delta_{njt} + \epsilon_{it}. \tag{3.2}$$

$\mathbb{1}[\text{Adopt}_{it}]$ is a first-time adoption dummy. We control for time-varying region-sector fixed effects δ_{njt}, so variation comes from differences between adopters and non-adopters within region-sectors.

Baseline results We consider two standard measures for firm performance, log sales and revenue-based TFP, as outcomes. Our revenue-based TFP (TFP^{rr}) is obtained as residuals from estimating the production function using the control function approach (Olley and Pakes, 1996; Ackerberg et al., 2015), where investment is used as a proxy variable.[10] We account for the possibility that adoption may affect the underlying TFP process by adapting the estimation procedure of De Loecker (2013).

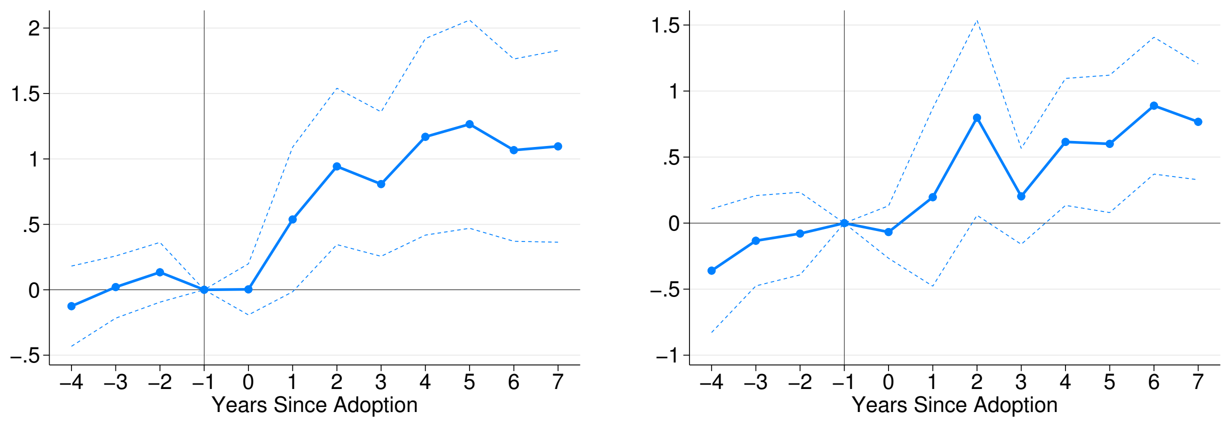
Table 1 and Figure 3 report the estimated coefficients in Equation (3.1). There were no pre-trends and winners' sales and TFP^{rr} begin to increase only after the adoption. 4 years after the adoption, winners' sales and TFP^{rr} experience increases of 120% and 68%, respectively, with persistent effects over time. On average, log sales and TFP^{rr} increased by 92% and 64% after the adoption.[11] The magnitude of our estimates is also consistent with the recent work by Giorcelli and Li (2021) who study the effects of technology transfers from the Soviet Union on Chinese steel plants during China's early industrial development.[12]

[10] It is important to note that TFP^{rr} differs from TFPR, as highlighted by Blackwood et al. (2021). While TFPR, calculated based on cost shares, is equalized across firms under monopolistic competition without distortions, TFP^{rr} is proportional to productivity. In our estimation, investment is computed as the difference between fixed assets of two consecutive periods, assuming a depreciation rate of 0.06.

[11] We calculate the average effects from the estimate of the following regression: $y_{it} = \beta(\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]) + \delta_{im} + \delta_{mt} + \epsilon_{imt}$, where $\mathbb{1}[\text{Post}_{mt}]$ is a dummy indicating the post-event periods. We obtain the estimated values of 0.92 and 0.64 with standard deviations of 0.33 and 0.25 for log sales and TFP^{rr}, which were statistically significant under the 1% and 5% levels, respectively.

[12] They find that technology transfers increased the TFPQ of Chinese steel plants by 25% after six years. Under

Figure 3. Direct Effects on Adopters: Winners vs. Losers Design



A. Log sales B. TFP^{rr}

Notes. This figure illustrates the estimated β_τ in Equation (3.1) based on the winners vs. losers research design. Panels A and B show the estimated coefficients for log sales and TFP^{rr} as dependent variables, respectively. All specifications control for match-year and match-firm fixed effects. The plotted coefficients are obtained from columns 1-2 of Table 1. The dotted lines represent the 90 percent confidence intervals based on standard errors clustered at the firm level.

The TWFE estimator also shows that adopters' sales increased after the adoption, but it exhibits increasing pre-trends at -4 and its magnitude was 75% smaller than that of the baseline. Despite the observed increase in sales, however, the TWFE estimates for TFP^{rr} remain flat after the adoption. The discrepancies between the baseline and TWFE estimators arise because the baseline corrects for the endogeneity problem. In fact, we provide evidence that subsidies are one source of the endogeneity that leads to the discrepancies. To investigate this, we include a dummy variable representing the receipt of credit (subsidy) from the government as an outcome. The TWFE coefficients are positive and statistically significant at the 1% level, suggesting that adopters were more likely to receive credit (column 6). However, the baseline estimators do not exhibit such a pattern (column 3). These findings are important for two reasons. First, they indicate that our winners vs. losers research design effectively addresses the endogeneity problem resulting from subsidies. Second, we can interpret the increases in sales and TFP^{rr} from the baseline as the *pure* effects of the adoption, separate from the *joint* effects of the adoption and subsidies. Suppose the government reclaimed subsidies from losers after cancellations. In that case, we would expect winners to receive more credit, and the estimated coefficients from the subsidy dummy would become statistically significantly positive after the adoption, as observed in the TWFE specification. However, we do not find such a pattern.

monopolistic competition, where $\text{TFPQ} \propto \frac{\ln \text{Sale}}{\sigma - 1}$ and commonly calibrated values of σ range from 3 to 4, our estimates

Table 1: Direct Effects on Adopters

Research Design	Winners vs. Losers			Full-sample TWFE		
Dep. Var.	Sale	TFP^{rr}	Subsidy	Sale	TFP^{rr}	Subsidy
	(1)	(2)	(3)	(4)	(5)	(6)
4 years before	–0.13	–0.36	0.08	–0.17***	0.02	0.01
	(0.18)	(0.28)	(0.08)	(0.05)	(0.07)	(0.01)
3 years before	0.02	–0.13	–0.01	–0.05	–0.01	0.00
	(0.14)	(0.21)	(0.08)	(0.05)	(0.06)	(0.01)
2 years before	0.13	–0.08	0.04	–0.03	0.02	0.02
	(0.14)	(0.19)	(0.08)	(0.05)	(0.06)	(0.01)
1 year before						
Year of event	0.00	–0.07	0.04	0.02	–0.03	0.02**
	(0.12)	(0.12)	(0.09)	(0.06)	(0.06)	(0.01)
1 year after	0.54	0.20	0.01	0.13	–0.05	0.04**
	(0.33)	(0.40)	(0.10)	(0.09)	(0.08)	(0.02)
2 years after	0.94**	0.80*	–0.04	0.23**	–0.02	0.03**
	(0.36)	(0.44)	(0.11)	(0.10)	(0.08)	(0.01)
3 years after	0.81**	0.20	0.13	0.18	–0.02	0.02
	(0.33)	(0.22)	(0.12)	(0.13)	(0.12)	(0.01)
4 years after	1.17**	0.62**	–0.04	0.26**	0.00	0.02
	(0.45)	(0.29)	(0.09)	(0.13)	(0.13)	(0.02)
5 years after	1.27***	0.60*	–0.03	0.30**	0.03	–0.02
	(0.48)	(0.31)	(0.09)	(0.14)	(0.17)	(0.02)
6 years after	1.07**	0.89***	–0.04	0.30**	0.08	0.02
	(0.42)	(0.31)	(0.10)	(0.14)	(0.11)	(0.02)
7 years after	1.10**	0.77***	–0.04	0.28*	0.07	–0.00
	(0.44)	(0.26)	(0.10)	(0.15)	(0.14)	(0.03)
Match×Firm FE	✓	✓	✓			
Match×Year FE	✓	✓	✓			
Firm FE				✓	✓	✓
Region×Sector×Year FE				✓	✓	✓
# Cl (Firm or Region)	91	80	91	77	55	77
N	644	484	644	24131	12657	24131

Notes. Standard errors in parentheses are clustered at the firm level in columns 1-3 or the region level in columns 4-6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Columns 1-3 and 4-6 report the estimated event study coefficients β_τ from the winners vs. losers research design (Equation (3.1)) and the full-sample TWFE (Equation (3.2)), respectively. β_{-1} is normalized to zero. The dependent variables are log sales, TFP^{rr}, or a dummy variable indicating the receipt of subsidy. Columns 1-3 control for match-firm and match-year fixed effects, while columns 4-6 control for firm and region-sector-year fixed effects.

for sales imply an increase in TFPQ by 35% to 57%.

Robustness We rule out alternative hypotheses against our findings. One possibility is that foreign firms sold technology tailored to their inputs, leading to increases in sales or TFP^{rr} due to technology-driven demand shocks from selling more inputs to these foreign technology sellers, rather than physical productivity gains. However, aggregate trade patterns, such as the decreasing import or export shares from Japan and the US (the two largest sources of foreign technology) during the sample period, make this alternative explanation unlikely (Appendix Figure B2). We also exclude the possibility of demand shocks due to government military spending, as none of the matched winners and losers were military firms. Finally, the raw plot of losers' sales exhibits similar trends before and after cancellations, suggesting that our estimates are driven by the positive gains of adopters rather than negative effects of cancellations on losers (Appendix Figure B1).[13]

Appendix Table B3 reports additional robustness exercises. We consider alternative outcomes. The adoption had positive impacts on labor productivity defined as sales divided by employment, and marginally increased the probability of exporting. Although marginally significant, the export results suggest that the adopters became productive enough to compete in global markets. We also consider alternative numbers of winners matched for each loser and two-way clustering at the levels of match and firm.

3.2 Local Spillovers

In this subsection, we show that technology adoption had local spillover effects. We define adopter shares in region-sector nj in year t as

$$\text{Share}_{(-i)nj,t-h} = \frac{N^T_{(-i)nj,t-h}}{N_{(-i)njt}}. \tag{3.3}$$

$N_{(-i)njt}$ is the total number of firms in region-sector nj in t excluding firm i. $N^T_{(-i)nj,t-h}$ is the number of firms operating in t that were in contract with any foreign firms in year $t-h$ excluding firm i. We construct $N^T_{(-i)nj,t-h}$ using information on contract years. We exclude i to rule out the mechanical correlation. Lagging by h years allows for the possibility that it took some time for the local diffusion of new knowledge from adopted technologies. We set the value of h to 2 as a baseline.

We consider a following long-difference specification:

$$\triangle y_{it} = \beta \triangle \text{Share}_{(-i)nj,t-2} + y_{it_0} + \mathbf{X}'_{injt}\gamma + \delta_n + \delta_j + \sum_g D_g \delta_{jg} + \triangle \epsilon_{it}, \tag{3.4}$$

where $\triangle$ is a time difference operator and i denotes firm, g business group, j sector, n region, and t year. Dependent variables y_{it} are changes in log sales or TFP^{rr}. Firm time-invariant factors are differenced out. δ_n and δ_j are region and sector fixed effects. D_g is a dummy of whether a firm is

[13] Increased local competition could potentially exert negative effects on losers. However, given that manufacturing sectors are highly tradable, and our spatial unit of analysis is very granular (matching firms within 135 sub-divided regions in a country the size of Indiana in the US), it is unlikely to have a significant impact.

affiliated with business group g that may own multiple firms across region-sectors. For firms affiliated with group g ($D_g = 1$), we control for group-sector fixed effects δ_{jg}, which absorb group-sector level common factors, such as within group-sector spillovers. In all specifications, we control for the initial level of the dependent variable due to the well-documented fact that larger firms grow less fast. Some specifications include additional observables $\mathbf{X}_{injt}$. We two-way cluster standard errors at the levels of regions and business groups. Individual firms not affiliated with any groups are subject to their own group-level clusters.

Note that the adopter shares can affect firm performance through spillovers but also through their influences on firms' adoption decisions. To restrict our attention to the former channel, the estimation sample only includes firms that never adopted technology. The estimates based on the never-adopter sample reflect only the spillovers because, by definition, they had not benefited from any direct effects of the adoption.

To use the data more efficiently, we use overlapping 7-year long-differences between 1972 and 1979 or 1973 and 1980, which cover the policy period. To deal with potential sorting, we estimate Equation (3.4) only for continuing firms, but firm entry and exit affect $\text{Share}_{(-i)nj,t-2}$.

IV strategy OLS estimates of Equation (3.4) may suffer from endogeneity due to correlations between the error term and region-sector level adopter shares. For example, unobserved region-sector level productivity or subsidy shocks that affect both firm growth and other local firms' adoption decisions can lead to such correlations. Also, the restriction to the never-adopter sample can cause a selection problem. However, the direction of the bias of OLS is a priori unclear. On the one hand, positive productivity shocks lead to an upward bias. On the other hand, if adoption subsidies were systematically provided to less productive but more politically-connected firms, subsidy shocks can lead to a downward bias. Also, as our data do not cover the universe of firms, measurement errors in local shares can be another source of the downward bias.

To address these concerns, we use the geographical structure of business groups with multiple firms across regions to construct an IV that isolates variation in local adopter shares, which is arguably exogenous to firm-level unobserved factors. This IV strategy follows Moretti (2021), who uses the spatial network of firms with multiple locations to construct exogenous shifters for local inventor cluster size.

Let $N^{\text{T},\geq 25\text{km}}_{g(-n)jt}$ represent the total number of sector j adopters affiliated with business group g in year t excluding firms that are located in region n or within 25km radius circles around region n. We define

$$Z^{\geq 25\text{km}}_{inj,t-h} = \sum_{\tilde{g} \neq g(i)} D_{\tilde{g}njt_0} \times \frac{N^{\text{T},\geq 25\text{km}}_{\tilde{g}(-n)j,t-h}}{\tilde{N}^{\text{p}}_{(-i)njt}},$$

where $D_{\tilde{g}njt_0}$ is a dummy variable indicating whether business group $\tilde{g}$ has at least one firm in region-sector nj in the initial year. $\tilde{N}^{\text{p}}_{(-i)njt}$ is the predicted number of firms in region-sector nj:

$\tilde{N}^{\mathrm{p}}_{(-i)njt} \equiv g_{(-n)jt} \times N_{(-i)njt_0}$, where $g_{(-n)jt}$ is national-level growth of the number of sector j firms, excluding those in region n, and $N_{(-i)njt_0}$ is the number of firms in region-sector nj, excluding firm i, in the initial year. We construct the IV as

$$\mathrm{IV}^{\geq 25\mathrm{km}}_{inj,t-h} = \triangle Z^{\geq 25\mathrm{km}}_{inj,t-h}. \tag{3.5}$$

We exclude firms located within 25km due to potential spatial interactions with neighboring firms through IO linkages or spatially correlated unobservables. Our IV varies at the level of business groups within region-sectors. Individual firms not affiliated with any groups share the same IV values, while firms affiliated with groups have different values from these individual firms because the summation excludes their own groups.

The explicit identifying assumption is that, for firm i, the variation in the number of adopters outside of firm i's region, which are affiliated with business groups owning a firm located in firm i's region in the initial year, is orthogonal to firm i's unobservables. To illustrate the intuition behind the IV, let's consider the Samsung Group as an example. The group owned six firms in the electronics sector, with four of them located in Suwon (the Northwestern region) and two in Ulsan (the Southeastern region), respectively. The underlying idea is that Samsung's adoption decisions at the group-level, outside of Ulsan, may increase the level of adoption in Ulsan through its affiliated firms located there. However, these group-level adoption decisions are not expected to be correlated with the productivity or subsidy shocks experienced by other firms in Ulsan that are not affiliated with the Samsung Group.

Baseline results Table 2 reports the estimation results. In Panel A, the dependent variable is sales growth. Column 1 reports the marginally significant OLS estimate. Column 2 reports the IV estimate, which is 4. This implies that one percentage point increase in adopter shares leads to 4% higher sales. The magnitude of the IV estimate is larger than the OLS estimate because the IV corrects for the measurement error and the endogeneity issues. The IV is strong with a first-stage coefficient of 0.17 and a Kleibergen-Paap F-statistics (KP-F) of 41. In Panel B, the dependent variable is $\mathrm{TFP}^{\mathrm{rr}}$ growth. Although the statistical significance weakens as the sample size decreases due to missing employment data, we find that one percentage point increase in adopter shares leads to 1.2% higher $\mathrm{TFP}^{\mathrm{rr}}$. Our firm-level analysis of local spillovers aligns broadly with the findings of previous studies (e.g. Greenstone et al., 2010; Giorcelli and Li, 2021). Furthermore, the observed limited competition effect is consistent with increased foreign demand and a substantial labor supply shift resulting from the reallocation of labor from the agricultural sector to the manufacturing sectors during the process of industrialization (Vogel, 1991; Lucas, 2004)

Additional controls Our main findings remain robust to additional controls. Because firms outside of region-sector nj can affect firm i's growth through IO linkages, in column 3, we control for

Table 2: Local Spillover

	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dep. $\triangle \ln \text{Sale}_{it}$ 1972-1979 or 1973-1980								
$\triangle\text{Share}_{(-i)nj,t-2}$	0.77*	3.99***	3.90***	4.16***	3.81***	3.88***	4.11***	3.88***
	(0.46)	(1.00)	(1.04)	(1.09)	(0.98)	(0.97)	(0.96)	(1.02)
KP-F		67.59	68.85	82.76	66.02	61.07	89.20	104.49
# Cl. (Region)	79	79	79	79	79	79	79	79
# Cl. (Group)	1294	1294	1294	1294	1294	1294	1294	1294
N	1492	1492	1492	1492	1492	1492	1492	1492
Panel B. Dep. $\triangle \ln \text{TFP}^{\text{rr}}_{it}$ 1972-1979 or 1973-1980								
$\triangle\text{Share}_{(-i)nj,t-2}$	−0.23	1.15*	1.00	1.26**	1.16**	1.11*	1.09*	0.95
	(0.29)	(0.58)	(0.60)	(0.60)	(0.58)	(0.57)	(0.60)	(0.68)
KP-F		64.68	69.11	79.10	56.32	62.20	93.41	114.49
# Cl. (Region)	67	67	67	67	67	67	67	67
# Cl. (Group)	742	742	742	742	742	742	742	742
N	824	824	824	824	824	824	824	824
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FEs	✓	✓	✓	✓	✓	✓	✓	✓
Market access			✓					✓
Own region-sector GO				✓				✓
Directed credit					✓			✓
Complex controls						✓		✓
Tariff controls							✓	✓

Notes. Standard errors in parentheses are two-way clustered at the levels of regions and business groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the OLS and IV estimates of Equation (3.4). The adoption shares and IV are defined in Equations (3.3) and (3.5), respectively. In Panels A and B, dependent variables are changes in log sales or TFP^{rr} between 1972 and 1979 or 1973 and 1980. In column 3, we include a control for market access defined in Equation (3.6). In column 4, we include a control for own region-sector gross output defined in Equation (3.7). In column 5, we include the inverse hyperbolic sine transformation of cumulative credit received between 1973 and 1979. In column 6, we include an industrial complex dummy. In column 7, we include interaction terms between port dummies and import and input tariffs. In column 8, we include all additional controls. All specifications include region, sector, and sector-group fixed effects, and initial levels of dependent variables. KP-F is the Kleibergen-Paap F-statistics.

market access measure defined as a weighted sum of other firms' sales, weighted by the inverse of the distance between firms (Donaldson and Hornbeck, 2016):

$$\triangle \ln \mathrm{MA}_{i(-nj)t} = \triangle \ln \Big(\sum_{m,k,mk \neq nj} \sum_{i' \in \mathcal{F}_{mkt}} \mathrm{Dist}_{nm}^{-\chi} \times \gamma_k^j \mathrm{Sales}_{i't} \Big), \tag{3.6}$$

where $\mathcal{F}_{mkt}$ is the set of firms in region-sector mk operating in year t. We proxy internal trade costs using distance between regions Dist_{nm}, and set χ to 1.1 (Costinot and Rodríguez-Clare, 2014). To mitigate the endogeneity concern, we exclude firm i's own region-sector.

It is possible that firms in regions with larger adopter shares experienced faster growth because due to their co-location with larger-sized firms. To separate the variation in adopter shares from the variation associated with co-location with large-sized firms, in column 4, we control for the sum of sales of firms within regions-sectors, defined as:

$$\triangle \ln \mathrm{GO}_{(-i)njt} = \triangle \ln \Big(\sum_{i' \in \mathcal{F}_{(-i)njt}} \mathrm{Sales}_{i't} \Big), \tag{3.7}$$

where $\mathcal{F}_{(-i)njt}$ is the set of firms in nj in t excluding i.

In column 5, to examine how subsidies affect our estimates, we control for the inverse hyperbolic sine transformation of the sum of directed credit received between 1972 and 1979 or 1973 and 1980. The magnitude of the estimate with the subsidy control is consistent with the baseline estimate in column 2. The stable coefficients support the exclusion restriction that the IV is uncorrelated with firm-level subsidy shocks.

During the policy period, the government constructed industrial complexes in the Southeastern regions and promoted heavy manufacturing firms in these complexes (Choi and Levchenko, 2023). Using information from the 1980 Yearbooks of Industrial Complexes published by the Korea Industrial Complex Corporation, we identify firms located in these complexes. We construct a dummy of whether firms were located in these complexes and include it as a control in column 6.

The government strongly promoted export-oriented development through trade policy (Connolly and Yi, 2015). The common effects of these trade policies are absorbed by the sector-fixed effects. However, the policies can have differential impacts across regions depending on how internal trade costs shield them from foreign competition. Reductions in import tariffs will increase the degree of foreign competition of firms located near ports relatively more than those located inland. In column 7, we include for a port dummy interacted with the changes in import tariffs. Additionally, because import tariffs can affect firm performance through the costs of imported intermediates, we also control for the port dummies interacted with the changes of input tariffs. We construct input tariffs as the weighted average of import tariffs, where the weights are given by the value share of inputs from the 1970 IO table. In column 8, we control for all these additional controls jointly.

Placebo To examine whether our results are driven by a spurious correlation between unobservables and the IV, we conduct the placebo exercise. We re-estimate the regression model using as dependent variables sales growth between 1970 and 1972 or 1971 and 1973. The intuition is that because the IV is an exogenous shifter for adopter shares between 1972 and 1979 or 1973 and 1980, the IV should not affect firm growth before these periods. We find that the coefficients are statistically insignificant, suggesting that the IV or future changes in the adopter shares do not predict the past sales growth (Appendix Table B4).

Functional form Our baseline specifications impose a linear relationship between log sales and the adopter shares. Also, the adopter shares are scale-free and the spillover effects do not vary across firms depending on their size. To explore the linearity, the scale-freeness, and the firm size heterogeneity, we add interaction terms between the changes in the adopter shares and a dummy whether initial levels of adopter shares, region-sectors' number of firms, and firm sales are above the 90th percentile, respectively. We instrument these additional interaction terms with interaction terms between our IV and the corresponding initial dummies. None of the interaction terms are precisely estimated, supporting our functional form (Appendix Table B5).[14]

Additional robustness checks We conduct a battery of robustness checks. We consider alternative outcomes and find positive effects of adopter shares on the probability of exporting and labor productivity. These positive effects support that never-adopters' productivity improved due to local spillovers. We also check sensitivity of not controlling for y_{it_0} and using an alternative lag of 3.

Variation in the IV comes from business groups that own multiple firms across regions within sectors. We push this leave-out logic further and re-estimate the regression model with the same IV only for a subsample of firms that are not affiliated with any business groups and are located in a single region by definition. We also consider a subsample that exclude firms in regions where heavy manufacturing industrial complexes are constructed, a single difference between 1973 and 1980, and the full sample including both adopters and never-adopters.

Additionally, when constructing the IV, we consider alternative radius circles with distances ranging from 0km to 150km.

3.3 Local Complementarity in Adoption Decisions

Local levels of the adoption could have affected firms' adoption decisions. To examine this relationship, we employ a similar overlapping long-difference regression model between 1972 and 1979 or

[14] Kline and Moretti (2014) also test nonlinearities in the agglomeration effects of manufacturing density using interaction terms between changes in the density and the initial density. They find the log-linear relationship between log employment and the density, implying that the agglomeration effects are log-linear or concave in the density. Unlike their paper, our data support the linear relationship between log sales and adopter shares, possibly due to the different sources of spillovers.

Table 3: Local Complementarity in Technology Adoption Decisions

Dep.	$\triangle\mathbb{1}[\text{New Contract}_{i,t+1}]$							
	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\triangle\text{Share}_{(-i)nj,t-2}$	-0.06	0.70***	0.69***	0.73**	0.73***	0.69***	0.69***	0.71**
	(0.11)	(0.26)	(0.26)	(0.28)	(0.27)	(0.25)	(0.26)	(0.28)
KP-F		35.09	33.69	39.79	34.97	31.71	45.79	47.42
# Cl. (Region)	86	86	86	86	86	86	86	86
# Cl. (Group)	1548	1548	1548	1548	1548	1548	1548	1548
N	1977	1977	1977	1977	1977	1977	1977	1977
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FEs	✓	✓	✓	✓	✓	✓	✓	✓
Market access			✓					✓
Own region-sector GO				✓				✓
Directed credit					✓			✓
Complex controls						✓		✓
Tariff controls							✓	✓

Notes. Standard errors in parenthesis are two-way clustered at the levels of regions and business groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the OLS and IV estimates of Equation (3.8). Adopter shares and IV are defined in Equations (3.3) and (3.5), respectively. The dependent variable is a dummy of making a new adoption contract in $t+1$ between 1972 and 1979 or 1973 and 1980. In column 3, we control for the market access defined in Equation (3.6). In column 4, we control for own region-sector gross output defined in Equation (3.7). In column 5, we control for the inverse hyperbolic sine transformation of cumulative credit received between 1973 and 1979. In column 6, we control for an industrial complex dummy. In column 7, we control for interaction terms between port dummies and import and input tariffs. In column 8, we control for all additional controls. All specifications include region, sector, and sector-group fixed effects, and initial levels of dependent variables. KP-F is the Kleibergen-Paap F-statistics.

1973 and 1980:

$$\triangle\mathbb{1}[\text{New Contract}_{i,t+1}] = \beta\triangle\text{Share}_{(-i)nj,t-2} + \mathbf{X}'_{injt}\gamma + \delta_n + \delta_j + \sum_g D_g\delta_{jg} + \triangle\epsilon_{it}. \tag{3.8}$$

Here, the dependent variable is a dummy variable indicating whether a firm made new adoption contracts in a given year, denoted as $\mathbb{1}[\text{New Contract}_{i,t+1}]$. Note that $\mathbb{1}[\text{New Contract}_{it}]$ differs from $\mathbb{1}[\text{Adopt}_{it}]$ that is used to construct the adopter shares. For example, if a firm had not adopted any foreign technologies previously but made a new contract in time t, both $\mathbb{1}[\text{New Contract}_{it}]$ and $\mathbb{1}[\text{Adopt}_{it}]$ become 1 in year t. Conversely, if a firm made a contract in year $t-3$ but did not make a new contract in year t, only $\mathbb{1}[\text{Adopt}_{it}]$ would take a value of 1.

Using the full sample, including both never-adopters and ever-adopters, we estimate Equation (3.8) with the same IV and the set of fixed effects as used in the spillover regression. The identifying assumption remains the same as that of the IV of the spillover regression. The positive β implies that firms were more likely to adopt new foreign technology if more local firms adopted technology. Standard errors are two-way clustered at the levels of regions and business groups.

Columns 1 and 2 of Table 3 report the OLS and IV estimates, respectively. Once endogeneity is corrected, the estimate becomes positive and statistically significant. The IV estimate suggests that a 1 percentage point increase in adopter shares leads to a 0.7 percentage point increase in the probability of making a new contract. The 0.7 percentage point increase represents approximately 12% of the average probability of making new contracts in 1979 and 1980 (6 percentage points). Columns 3-8 of Table 3 include the same set of additional controls used in the spillover regression. Across different specifications, the estimates remain positive, statistically significant, and exhibit stable magnitudes.

IV validity and robustness checks We conduct a placebo test with changes in the new contract dummy before 1973. The results show no statistically significant relationship (Columns 4-6 of Appendix Table B4). Additionally, we perform a set of robustness checks similar to those conducted in the spillover regression (Appendix Table B7).

3.4 Summary and Discussion

To summarize, our analysis demonstrates that the adoption of foreign technologies had positive effects on both sales and TFP^{rr}, not only for adopters themselves but also for non-adopters through local spillovers. This indicates the potential presence of positive externalities associated with technology adoption. Furthermore, the observed complementarity in adoption decisions suggests the existence of a vicious circle, where firms are more likely to adopt foreign technologies if more local firms have already adopted them. If the one-time big push had triggered this vicious circle, firms would have continued to adopt foreign technologies even after subsidies are no longer provided, driven by the local complementarity. This big push story and the local effects of the adoption are consistent with the rapid industrialization process and the geographical concentration of adoption activities, as illustrated in Figures 1 and 2. In the next section, we formally explore the possibility of the big push for technology adoption.

4 A Simple Model of Technology Adoption and Multiple Equilibria

We present a simple dynamic model of firms' technology adoption decisions. The model generates features that are consistent with the three empirical findings. We analytically show that these findings, embodied in the model, can induce an economy to have multiple steady states. When multiple steady states exist, a big push that temporarily provides subsidies for technology adoption can have a large impact by shifting the economy from one steady state to the other. Later, we extend this simple model and quantitatively explore the effects of the big push.

Environment We consider a closed economy with one sector and one region. Time is discrete and indexed by $t \in \{1, 2, \ldots\}$. There is a fixed mass of monopolistically competitive firms indexed by i, with the mass M normalized to one. Each firm produces a unique variety ω. A final goods producer aggregates these varieties using the CES aggregator and produces final consumption goods. Labor is the only factor of production, and households inelastically supply labor.

Firm Each firm faces demand curves $q_{it} = p_{it}^{-\sigma} P_t^{\sigma} Q_t$ where q_{it} is their quantity demanded, p_{it} is the price charged by them, $Q_t = (\int (q_{it}(\omega))^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega)^{\frac{\sigma}{\sigma-1}}$ is the aggregate quantity, and $P_t = (\int_{\omega} (p_{it}(\omega))^{1-\sigma} \mathrm{d}\omega)^{\frac{1}{1-\sigma}}$ is the ideal price index. $\sigma > 1$ is the elasticity of substitution across varieties. Firms optimally charge constant markups $\mu = \sigma/(\sigma-1)$ over its unit costs $p_{it} = w_t/z_{it}$, where z_{it} is firm productivity.

Firms are heterogeneous in productivity, and their decisions to adopt modern technology and spillovers from technology adoption endogenously determine their productivity in the equilibrium. Firm productivity is composed of three terms:

$$z_{it} \equiv z_{it}(T_{it}, \lambda_{t-1}^{T}) = \eta^{T_{it}} \times f(\lambda_{t-1}^{T}) \times \phi_{it},$$

where T_{it} is a binary variable that equals one if a firm adopts modern technology. The first term $\eta > 1$ governs direct productivity gains from the adoption. The second term $f(\lambda_{t-1}^{T})$, common across firms, is the adoption spillover that increases with the adopter share in the previous period λ_{t-1}^{T}. In Appendix Section C.4, we provide two sets of microfoundations that generate the spillovers through labor mobility and knowledge transfers.[15] The third term ϕ_{it} is exogenous productivity, independently and identically distributed across firms and periods. The first and second terms are motivated by the first and second empirical evidence.

We consider the following functional form for the spillover:

$$f(\lambda_{t-1}^{T}) = exp(\delta \lambda_{t-1}^{T}),$$

where δ is a parameter that governs the strength of the spillover. Following Kline and Moretti (2014) and Allen and Donaldson (2020), we allow the spillover to operate with a one-period lag rather than contemporaneously. The chosen functional form and the inclusion of a lag in the spillover effect align with the specification of the spillover regression and the robustness check on the linear relationship between log sales and adopter shares and the scale-freeness of adopter shares. We view that allowing for a lag is more realistic because it may take some time for knowledge to be locally diffused. Also,

[15] In the first setup, we consider a setup in which engineers and firms are randomly matched (Acemoglu, 1996), and engineers carry new knowledge learned from adopted technologies when matched with a new firm in the next period. In the second setup, we present a model by Desmet and Rossi-Hansberg (2014), where own innovation costs become lower with higher adopter shares due to knowledge transfers.

as discussed by Adserà and Ray (1998), allowing for a lag yields an economy to have a deterministic outcome each period, preventing the economy from experiencing unrealistic fluctuations where it alternates between different outcomes in every period.

The adoption incurs fixed costs F^T in units of final goods (Buera et al., 2021). Firms adopt technology when additional operating profits from the adoption are larger than the fixed costs:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} \left\{ \frac{1}{\sigma} \frac{\mu w_t}{z_{it}(T_{it}, \lambda^T_{t-1})} P^\sigma_t Q_t - T_{it} P_t F^T \right\},$$

where π_{it} is i's final profits. When making adoption decisions, firms internalize the direct productivity gains η but not the spillovers $f(\lambda^T_{t-1})$ and take λ^T_{t-1} as given in t. Due to this externality, the social returns to the adoption exceed the private returns, leading to suboptimal adoption rates below the socially optimal level.

With heterogeneous productivity, adoption decisions are characterized by the following cutoff productivity:

$$(\bar{\phi}^T_t)^{\sigma-1} = \frac{\sigma P_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma} f(\lambda^T_{t-1})^{\sigma-1} P^\sigma_t Q_t}. \tag{4.1}$$

Only firms with productivity higher than the cutoff chose to adopt technology. The adoption probability is $\lambda^T_t = \mathbb{P}[\phi_{it} \geq \bar{\phi}_t]$, equivalent to the adopter shares with the normalized firm mass.

Equilibrium In each period, given λ^T_{t-1}, firms adopt technology to maximize their profits and goods and factor markets clear (static equilibrium). λ^T_t is a state variable that endogenously evolves based on firms' adoption decisions (dynamic equilibrium). Given λ^T_{t-1}, the equilibrium share λ^{T*}_t is determined in t; and then given λ^{T*}_t, λ^{T*}_{t+1} is determined in $t+1$; and so on.

We impose the following assumptions:

Assumption 1. *(i) $\sigma > 2$; and (ii) ϕ_{it} follows the Pareto distribution with the location parameter normalized to be one and the shape parameter θ.*

Under the Pareto productivity distribution, the cutoff can be expressed as

$$\bar{\phi}^T_t = (\lambda^T_t)^{-\frac{1}{\theta}}. \tag{4.2}$$

By combining Equations (4.1) and (4.2), we can derive the analytical expression of the equilibrium adopter shares $\lambda^{T*}_t = \lambda^{T*}_t(\lambda^T_{t-1}; \eta, \delta)$ in each period conditional on λ^T_{t-1}. The equilibrium shares are determined at

$$\lambda^{T*}_t(\lambda^T_{t-1}; \eta, \delta) = \min\{\hat{\lambda}^T_t(\lambda^T_{t-1}; \eta, \delta), 1\}, \tag{4.3}$$

where $\hat{\lambda}_t^T(\lambda_{t-1}^T;\eta,\delta)$ is implicitly defined by

$$\hat{\lambda}_t^T(\lambda_{t-1}^T;\eta,\delta) = \left[A(\hat{\lambda}_t^T(\lambda_{t-1}^T;\eta,\delta))^{2-\sigma}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}f(\lambda_{t-1}^T)\right]^{\frac{\theta}{\sigma-1}},$$

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

The time-invariant steady state adopter shares ($\lambda^{T*} = \lambda_t^{T*} = \lambda_{t-1}^{T*}$) satisfy $\lambda^{T*} = \lambda^{T*}(\lambda^{T*};\eta,\delta)$.

Equilibrium properties and multiple equilibria Assumption (i) ensures the unique static equilibrium each period.[16] Given any initial adopter shares λ_{t_0}, because static equilibrium is unique each period, there exists a unique sequence of static equilibria that forms a unique deterministic dynamic path from λ_{t_0} to a steady state.

The dynamic path of λ_t^T is characterized by dynamic complementarity in firms' adoption decisions. Dynamic complementarity means that λ_t^{T*} increases with λ_{t-1}^T. When more firms adopt technology in the previous period, firms are more likely to adopt technology, it increases the likelihood of other firms adopting technology in the current period, consistent with the third empirical finding. The fixed adoption costs being measured in units of final goods are the source of this complementarity. The spillover from the previous period's adoption shares lowers P_t of the current period and therefore reduces total expenditures on fixed adoption costs in the current period (P_tF^T), further incentivizing more firms to adopt technology. Moreover, the equilibrium adoption share λ_t^{T*} increases with higher values of η and δ. Higher values of η magnify the direct gains from adoption, while higher values of δ strengthen the dynamic complementarity.

Importantly, we show that multiple steady states can arise from dynamic complementarity. When these steady states exist, they can be Pareto-ranked based on the steady state share of adopters. The initial adoption share determines which steady state will be realized in the long-run, implying path dependence. Proposition 1 summarizes these results.

Proposition 1. *Under Assumption 1,*

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

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

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

[16] When σ is sufficiently low, even when $\delta = 0$, because firms do not internalize P_t, two static equilibria, one with higher adopter shares and the other with lower shares, can arise. Higher shares increase competition but also decrease fixed adoption costs by lowering P_t, which incentivizes more and less adoption, respectively. $A(\lambda_t^T)^{2-\sigma} = A(\lambda_t^T)^{1-\sigma} \times A(\lambda_t^T)$ is related to these two general equilibrium effects that operate in the opposite directions. $A(\lambda_t^T)^{1-\sigma}$ captures the former and $A(\lambda_t^T)$ the latter. Lower σ makes competition effects weaker and more firms adopt technology with higher shares, which generates static complementarity and, in turn, potential multiple static equilibria. By imposing $\sigma > 2$, we make the competition effects sufficiently strong to rule out such possibility studied by Matsuyama (1995) and Buera et al. (2021). Unlike these papers, in our model, because we impose $\sigma > 2$, multiple long-run steady states arise only because of the spillovers. Also, commonly calibrated parameter values for σ are larger than 2.

(iv) (Multiple equilibria) There exists an interval $[\underline{\delta}, \bar{\delta}]$ $([\underline{\eta}, \bar{\eta}])$ *such that holding other parameters constant, multiple steady states arise only for* $\delta \in [\underline{\delta}, \bar{\delta}]$ $(\eta \in [\underline{\eta}, \bar{\eta}])$*;*

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

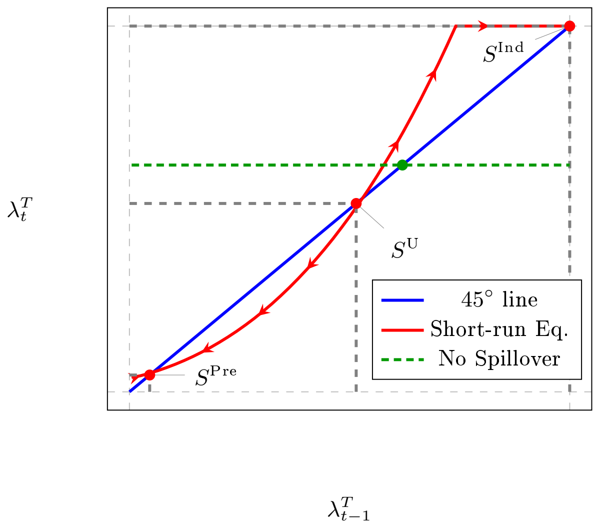
The case of multiple steady states is illustrated in Panel A of Figure 4 which shows three different steady states with two basins of attraction.[17] The red locus is defined by Equation (4.3). Each point on the locus represents a short-run equilibrium given λ^T_{t-1} and the equilibrium moves along the red locus as time passes. The steady state is determined at the point where $\lambda^{T*}_{t-1} = \lambda^{T*}_t, \forall t$ holds, i.e., where the red locus intersects the 45-degree blue line. There are three intersection points, labeled as S^{Pre}, S^{U}, and S^{Ind}, representing the pre-industrialized, unstable, and industrialized steady states, respectively. S^{U} is unstable in a sense that the economy converges to S^{U} only when the initial condition is equal to the value of S^{U}, so we exclude S^{U} from our focus.

These steady states can be Pareto-ranked depending on their adopter shares. At S^{Ind}, all firms adopt technology, while S^{Pre} has smaller adopter shares compared to the other two states, making S^{Ind} Pareto-dominant over S^{Pre}. The nonlinearity of the red locus is crucial in generating multiple steady states because it allows the locus to intersect the 45-degree line multiple times.[18] The spillover effect ($\delta > 0$) generates such nonlinearity. Without spillovers ($\delta = 0$), the equilibrium adopter share is determined each period regardless of the previous share, resulting in a unique steady state indicated by the intersection of the green dashed horizontal line and the 45-degree line.

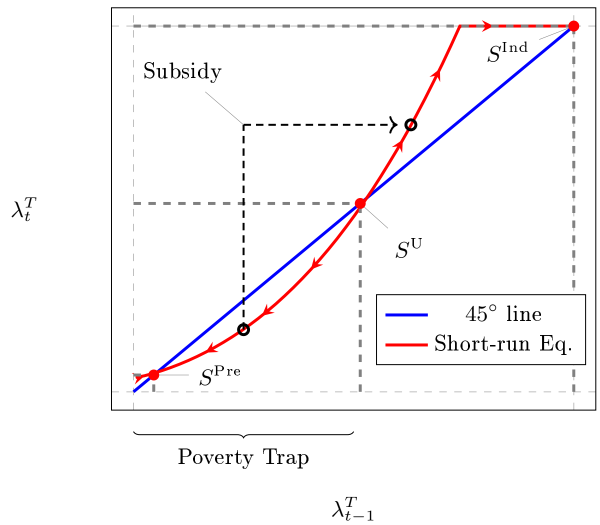
Poverty trap and big push When multiple steady states exist, initial conditions determine which steady state is realized. If the initial conditions are given by $\lambda^T_{njt_0} \in [0, S^{\text{U}})$ and $\lambda^T_{njt_0} \in (S^{\text{U}}, 1]$, the economy converges to S^{Pre} and S^{Ind}, respectively. The range $[0, S^{\text{U}})$ is commonly referred to as a poverty trap in the literature (Azariadis and Stachurski, 2005; Banerjee and Duflo, 2005). Suppose multiple steady states exist and an initial condition is trapped in the poverty trap, as shown in Panel B. In such a case, a big push policy that provides one-time subsidies for adopters' input costs or fixed adoption costs can have permanent effects by moving the economy out of the poverty trap. This is summarized in Proposition 2. The possibility of a big push is consistent with the narrative of South Korea's experience. It is important to note that, in this model, only multiple steady states can rationalize the permanent effects of a one-time policy. With a unique steady state, one-time subsidies would temporarily shift the short-run equilibrium curve, but the economy would ultimately converge back to its original steady state once the subsidies end.

[17] In this economy, there can be at most three multiple steady states due to the strict convexity imposed by the assumed spillover functional form. The functional form ensures that $\lambda^T t$ is strictly convex in $\lambda^T t - 1$, allowing the red locus in Figure 4 to intersect the 45-degree line at most twice. Alternative functional forms that generate higher levels of nonlinearity can result in more than three multiple steady states.

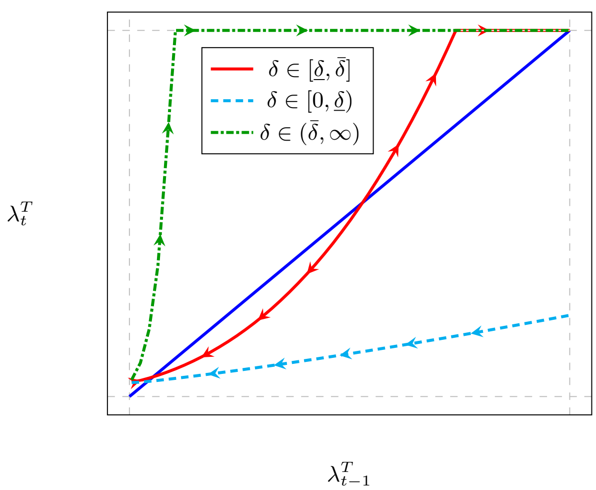
[18] Kline and Moretti (2014) did not detect sufficient nonlinearities in the agglomeration function that can generate multiple steady states, so they concluded that the Tennessee Valley Authority program did not have permanent effects through the big push.



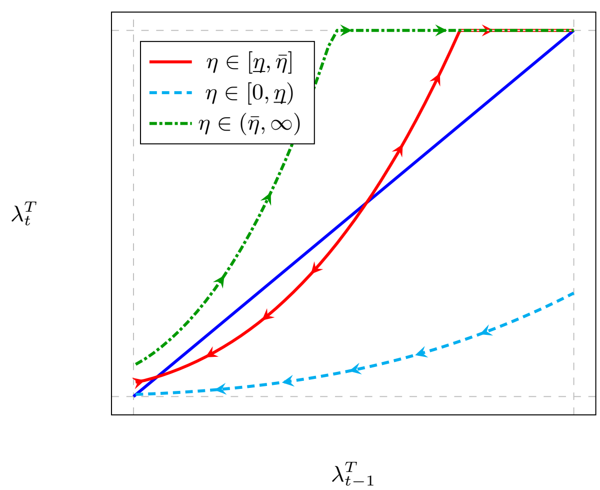
Panel A. Multiple Steady States and Nonlinearity



Panel B. Poverty Trap and the Big Push



Panel C. Comparative Statistics of δ



Panel D. Comparative Statistics of η

Figure 4. Multiple Steady States and the Big Push

Notes. Panel A illustrates that multiple steady states arise when the short-run equilibrium curve is sufficiently non-linear. Panel B illustrates that the big push can move an economy out of the poverty trap. Panels C and D illustrate that multiple steady states arise only for the medium range of values of η and δ, respectively.

Proposition 2. *(Big push) Suppose the multiple steady states exist and the economy is initially in the poverty trap, $\lambda^T_{t_0} \in [0, S^U)$. There exists a threshold $\underline{s}$ such that a one-time subsidy for adopters' input costs or fixed adoption costs that satisfy $s_t > \underline{s}$ can move an economy out of the poverty trap.*

Comparative statistics What determines this multiplicity? The existence of multiple steady states depends on values of the two key parameters δ and η (Proposition 1(iv)). Multiple steady states arise only for medium ranges of $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$, meaning that the spillovers or the direct productivity gains are neither too strong nor too weak (Panels C and D). If δ is too high or too low, it leads to excessively strong or weak dynamic complementarity, causing the short-run locus to become insufficiently nonlinear and intersect the 45-degree line only once. Similarly, if η is too high, firms experience substantial private returns from the adoption, resulting in more firms adopting the technology regardless of the previous shares, and vice versa. This leads to a single intersection point. These comparative statistics of δ and η provide a potential explanation for why the South Korean economy underwent a remarkable transformation towards heavy manufacturing sectors following the big push while other developing countries did not. The values of δ and η may depend on country-specific features, and South Korea could have been a special case where their values fell within a range that generated multiple steady states.[19]

5 Taking the Model to the Data

5.1 Quantitative Model

We extend the simple model and develop a quantitative framework to quantify the effects of the big push policy. Appendix Section D provides further details.

Geography, sectors, and trade We divide the world into Home and Foreign (H and F). Home is a small open economy that cannot affect Foreign aggregates. Home has multiple regions indexed by $n, m \in \{1, \ldots, N\} \equiv \mathcal{N}$ and multiple sectors indexed by $j, k \in \{1, \ldots, J\} \equiv \mathcal{J}$. Each sector j variety is tradable across regions and countries, subject to iceberg costs $\tau_{nmj} \geq 1$ and $\tau^x_{nj} \geq 1$, respectively.

In each region-sector, there is a fixed mass of monopolistically competitive firms M_{nj} and perfectly competitive final goods producers who produce nontradable local sectoral aggregate goods Q_{njt} used for final consumption and for intermediate inputs. These final good producers aggregate all available varieties from all regions and countries using a CES aggregator with the price index given by

$$P_{njt} = \left[\sum_m \int_{\omega \in \Omega_{mj}} (p_{njt}(\omega))^{1-\sigma} \mathrm{d}\omega + (\tau^x_{nj}(1+t_{jt})P^f_{jt})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{5.1}$$

$p_{njt}(\omega)$ is a price charged by firms, and Ω_{mj} is the set of available sector j varieties in region m.

[19] η can be related to the absorptive capacity of new technology, and δ to the degree of barriers for knowledge diffusion. For example, countries with lower levels of skilled labor or higher language barriers may have lower values of η or δ, respectively. Compared to other developing countries, South Korea had higher levels of skilled labor and used the same language (Rodrik, 1995), which could have resulted in higher values of η and δ.

Because there are no fixed export costs for internal trade, each region has the same set of available varieties. P^f_{jt} is a exogenous price of the foreign varieties and t_{jt} is an import tariff.

Home firms take foreign demands D^x_{jt} as exogenously given and face the demand schedule of $p_{it}^{-\sigma}D^x_{jt}$. D^x_{jt} also capture any common barriers for exporting. For example, export-promotion policies that reduced barriers for exporting will be captured by changes in D^x_{jt}. When exporting to Foreign, firms incur fixed export costs F^x_j in units of labor (Melitz, 2003). Note that unlike the fixed adoption costs, fixed export costs are not subject to the dynamic complementarity because they are not in units of final goods.

Production Firms have constant return to scale (CRS) Cobb-Douglas production, which requires intermediate inputs for their production. For firm i in sector j, the production function is given by

$$y_{it} = z_{it} L_{it}^{\gamma_j^L} \prod_k (M_{it}^k)^{\gamma_j^k}, \qquad \gamma_j^L + \sum_k \gamma_j^k = 1.$$

L_{it} represents labor inputs, and M_i^k sector k intermediate inputs.

The productivity term z_{it} consists of three components as in the simple model, but the spillover $f(\lambda_{nj,t-1})$ increases in the previous region-sector adopter shares, and ϕ_{it} follows the bounded Pareto distribution:

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

parametrized by $\phi_{njt}^{\max}$, $\phi_{njt}^{\min}$, and θ. The bounded Pareto rationalizes zero adoption regions in the data.[20] We assume that the gap between the lower and upper bounds of the distribution is constant across regions, sectors, and periods: $\phi_{njt}^{\max} = \kappa\phi_{njt}^{\min}$, parametrized by κ. The lower bounds vary across regions, sectors, and periods, but the upper bounds are always proportional to the lower bounds by κ.[21] $\phi_{njt}^{\min}$ is related to natural advantage. Any region-sector level productivity shifters that cannot be explained by technology adoption, such as the construction of industrial complexes, are rationalized by $\phi_{njt}^{\min}$

Adoption cost and subsidy We model the adoption subsidies as input subsidies $0 \leq s_{njt} \leq 1$, which may vary across regions, sectors, and periods.[22] With subsidies, adopters' input costs are

$$(1 - s_{njt})[w_{nt}L_{it} + \sum_j P_{njt}M_{it}].$$

[20] If the adoption cutoff productivity is above $\phi_{njt}^{\max}$, no firms in nj adopt technology. Similarly, Helpman et al. (2008) assume the same distribution to rationalize zero trade flows.

[21] The unbounded Pareto is a special case of the bounded Pareto. If $\kappa \to \infty$, the bounded Pareto collapses to the unbounded Pareto.

[22] This is based on the fact that the government provided subsidies to large adopters so they could purchase capital equipment related to adopted technologies, and we interpret new capital equipment as intermediate inputs in our model.

The government imposes a common labor tax τ_t^w to finance these subsidies and the after-tax wage in region n is $(1-\tau_t^w)w_{nt}$.[23] The government budget is balanced every period.

We assume that goods required for the fixed adoption costs F_{nj}^T are produced using the following Cobb-Douglas technology similar to production function:

$$L_{it}^{\gamma_j^L}\prod_k (M_{it}^k)^{\gamma_j^k} \times F_{nj}^T,$$

where γ_j^L and γ_j^k are Cobb-Douglas shares of production function.[24] Because parts of the fixed adoption costs are in units of final goods, the dynamic complementarity arises. F_{nj}^T potentially vary across region-sectors. Firms' cost minimization implies that total expenditures on fixed adoption costs are $c_{njt}F_{nj}^T$.

Household preference and migration In each region, there is a competitive labor market and wages are equalized across sectors. Households supply labor inelastically. We normalize the total population of the Home regions to 1. Households have Cobb-Douglas preferences over final consumption baskets, with the shares $\sum_j \alpha_j = 1$. They are subject to budget constraints: $P_{nt}C_{nt} = (1-\tau_t^w+\bar{\pi}_t)w_{nt}$, where C_{nt} is Cobb-Douglas consumption baskets and P_{nt} is the price index for these baskets. $(1-\tau_t^w+\bar{\pi}_t)w_{nt}$ is the total income of households, which is the sum of after-tax wages $(1-\tau_t^w)w_{nt}$ and income from dividends $\bar{\pi}_t^h w_{nt}$.

At the beginning of each period, households make *myopic* migration decisions and then they supply labor and earn wages in new regions where they have chosen to live. They maximize their static utility by choosing a location that maximizes their static utility each period: $\max_n\{U_{mnt}^h(\epsilon_{mnt}^h)\}$, where $\mathcal{U}_{mnt}^h(\epsilon_{mnt}^h)$ represents the utility of a household h that lived in n and moves to m in t:

$$\mathcal{U}_{nmt}^h(\epsilon_{nmt}^h) = V_{mt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{mt}}{P_{mt}}d_{nm}\epsilon_{nmt}^h.$$

V_{mt} is an exogenous amenity in m that captures characteristics that make regions more or less attractive to live in. d_{nm} represents the utility costs of moving from n to m. ϵ_{nmt}^h is a preference shock drawn i.i.d. from a Fréchet distribution with the shape parameter ν: $F(\epsilon) = exp(\epsilon^{-\nu})$ (Eaton and Kortum, 2002). The share of households moving from n to m in t is

$$\mu_{nmt} = \frac{\left(V_{mt}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{mt}}{P_{mt}}d_{nm}\right)^\nu}{\sum_{m'}\left(V_{m't}\frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{m't}}{P_{m't}}d_{nm'}\right)^\nu}.$$

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

[24]We assign the Cobb-Douglas shares identical to those in the production function due to the lack of detailed information regarding intermediate goods used for these fixed adoption costs.

ν is migration elasticity that governs the responsiveness of migration flows to real income changes in the destination. The population of each region evolves according to $L_{mt} = \sum_n \mu_{nmt} L_{n,t-1}$.

We define the regional welfare of households living in region n in time t as the expected static utility before the realization of the preference shocks (Allen and Donaldson, 2020):

$$U_{nt} = \left[\sum_m \left(V_{mt} \frac{(1 - \tau_t^x + \bar{\pi}_t^h) w_{mt}}{P_{mt}} d_{nm} \right)^\nu \right]^{\frac{1}{\nu}}. \tag{5.2}$$

The aggregate welfare is defined as the population-weighted average of U_{nt}: $U_t^{\text{agg}} \equiv \sum_n \frac{L_{nt}}{L_t} U_{nt}$.

Equilibrium In the equilibrium, given initial conditions $\{\lambda^T_{njt_0}, L_{nt_0}\}$ and a path of the fundamentals $\{\phi^{\min}_{njt}, V_{nt}, P^f_{jt}, D^x_{jt}\}$, tariffs $\{t_{jt}\}$, and subsidies $\{s_{njt}\}$, firms maximize profits; households maximize utility; labor and goods markets clear; trade is balanced, and the government budget is balanced; and firms' adoption and households' migration decisions endogenously determine the path of state variables λ_{njt} and L_{nt}.

5.2 Calibration

Each period corresponds to 4 years in the data. We aggregate sectors into four categories: commodity, light and heavy manufacturing, and service sectors. Commodity and manufacturing sectors are tradable both internally and internationally, whereas the service sector is non-tradable across regions and countries. Because most of the adoption occurred in the heavy manufacturing sectors, we assume that technology adoption is available only for the heavy manufacturing sector.

We calibrate our model to the period between 1972 and 1980. We take initial adopter shares $\lambda^T_{nj,68}$ and population $L_{n,68}$ directly from the data.[25] Given these initial values, we solve the model for $t = 1$ corresponding to 1972 in the data. After solving for $t = 1$, given values of λ_{nj1} and L_{n1}, we obtain the equilibrium λ_{nj1} and L_{n1}, and solve for $t = 2$, and so on. After $t = 3$, fundamentals are held constant at the levels of 1980. We sequentially solve the model period by period for large enough T until the model converges to a steady state.

We calibrate subsidies s_{njt}, tariffs t_{jt}, fundamentals $\mathbf{\Psi}_t$, and the following set of structural parameters

$$\mathbf{\Theta} = \{ \underbrace{M_{nj}}_{\substack{\text{Fixed} \\ \text{firm mass}}}, \underbrace{\theta, \kappa}_{\substack{\text{Pareto} \\ \text{distribution}}}, \underbrace{\eta, \delta, F^T_{nj}}_{\substack{\text{Technology} \\ \text{adoption}}}, \underbrace{\sigma, \gamma^k_j, \gamma^L_j}_{\text{Production}}, \underbrace{\tau_{nmj}, \tau^x_{nj}, F^x_j}_{\text{Trade costs}}, \underbrace{\nu, d_{nm}}_{\text{Migration}}, \underbrace{\alpha_j}_{\text{Preference}} \}.$$

We divide $\mathbf{\Theta}$ into two subgroups, $\mathbf{\Theta}^{\text{E}} = \{\eta, \delta, M_{nj}, \theta, \sigma, \gamma^L_j, \gamma^k_j, \nu, d_{nm}, \tau_{nmj}, \tau^x_{nj}, \alpha_j\}$ and $\mathbf{\Theta}^{\text{M}} = \{\kappa, F^x_j, F^T_{nj}\}$ depending on whether they are externally or internally calibrated, respectively. We externally calibrate $\mathbf{\Theta}^{\text{E}}$ and t_{jt}, and internally calibrate s_{njt}, $\mathbf{\Psi}_t$, and $\mathbf{\Theta}^{\text{M}}$ by indirect inference.

[25] While our firm balance sheet data covers from 1970 to 1982, technology adoption contracts cover from 1962 to 1985. Using the information on the start year of firms, we construct the adopter shares in 1968.

Table 4: Calibration Strategy

	Description	Value	Identification / Moments
		External calibration	
η	Direct productivity gains	1.35	Winners vs. losers, Table 1
δ	Spillover semi-elasticity	1.3	Spillover estimate, Table 2
σ	Elasticity of substitution	4	Broda and Weinstein (2006)
θ	Pareto shape parameter	3.18	Axtell (2001)
ν	Migration elasticity	2	Peters (2021)
ζ	Distance migration cost elasticity	0.78	Gravity estimates
ξ	Distance trade cost elasticity	0.43	Monte et al. (2018)
α_j	Preferences		IO table
γ_j^k	Production		IO table
M_{nj}	Exogenous firm mass		Value added (Chaney, 2008)
		Internal calibration	
φ_{j0}^T	Fixed adoption cost	1.8e-4	Avg. adopter shares, 72
φ_{j1}^T	Fixed adoption cost, dist. to port	1.5e-4	PPML, adopter share & dist. to port
F_j^x	Fixed export cost, comm., light mfg.	0.39	Exporter share, light mfg.
F_j^x	Fixed export cost, heavy mfg.	0.33	Exporter share, heavy mfg.
κ	Pareto upper bound	1.50	Share of regions with adoption
$\bar{s}$	Subsidy rate	0.08	Avg. adopter shares, 76 and 80
$\phi_{njt}^{\min}$	Natural advantage		Region-sector GO
D_{jt}^x	Foreign market size		Export intensity
P_{jt}^f	Foreign import cost		Import share
V_{nt}	Amenity		Pop. dist.

Notes. This table reports calibrated objects of the model, their values, and their identifying moments.

Table 4 summarizes our calibration strategy. Appendix Section E.1 explains the procedure in detail.

5.2.1 External Calibration

Elasticity of substitution We set the elasticity of substitution σ to 4 following Broda and Weinstein (2006).

Technology adoption By taking a log of adopters' sales, we derive the following relationship that can be mapped to the winners vs. losers specification (Equation (3.1)):

$$\ln \text{Sales}_{it} = (\sigma - 1) \ln \eta T_{it} + \delta_{mt} + (\sigma - 1) \ln \phi_{it}.$$

Match-year fixed effects δ_{mt} capture variables common at the match levels, including local spillovers, unit costs of production, and market size common across firms within region-sectors.[26] Also, based on the lack of evidence that winners received more subsidies relative to losers, we map the estimates to pure effects of technology adoption rather than joint effects including subsidies, and subsidies will be absorbed out by δ_{mt}.[27] From this mapping, we set $\eta = \exp(\frac{0.9}{\sigma-1}) = 1.35$, where 0.9 corresponds to the average effects of the adoption (column 1 of Table 1).

Taking log on non-adopters' sales, we obtain the following relationship that can be mapped to the spillover regression (Equation (3.4)):

$$\ln \text{Sales}_{it} = (\sigma - 1)\delta\lambda^T_{njt} + \mathbf{X}'_{njt}\boldsymbol{\gamma} + (\sigma - 1)\ln\phi_{it},$$

where $\mathbf{X}_{njt}$ are region-sector controls including unit cost and market access terms. From this relationship, we pin down δ to be $3.9/(\sigma - 1) = 1.3$, where 3.9 corresponds to the average of the IV estimates of columns 2-8 in Panel A of Table 2.

An alternative mapping based on $\text{TFP}^{\text{rr}}_{it} \propto \frac{\sigma-1}{\sigma}\ln z_{it}$ gives similar value for δ but larger value for η ($\eta = 2.2$ and $\delta = 1.5$).[28] Thus, the baseline calibrated values are lower bounds among the possible mappings.

Migration We parametrize migration costs as $d_{nm} = (\text{Dist}_{nm})^{\zeta}$, where Dist_{nm} is the distance between regions n and m. We set ν to 2 (Peters, 2021).[29] We derive a gravity equation for migration flows and estimate the equation using migration flows of people aged 20 to 55 from 1990 to 1995 obtained from the 1995 Population and Housing Census, which was the closest to the sample period among the accessible population census data. To address attenuation bias arising from statistical zeros in the gravity models, we estimate the equation using the Poisson Pseudo Maximum likelihood (PPML) (Silva and Tenreyro, 2006). We run $\mu_{nm} = exp(\nu\zeta \times \text{Dist}_{nm} + \delta_n + \delta_m) \times \epsilon_{nmt}$, where standard errors are two-way clustered at the origin and destination levels. The gravity estimate is $\nu\zeta = 1.39$ and statistically significant under the 1%.

Iceberg costs and tariffs We parametrize internal iceberg costs as $\tau_{nmj} = (\text{Dist}_{nm})^{\xi_j}$ where ξ_j is sector-specific distance elasticity. We set $\xi_j = 1.29/(\sigma - 1)$ for tradable sectors (Monte et al., 2018). We assume that firms have to ship their products to the nearest port and then pay both iceberg and fixed trade costs at the port when they export and parametrize international iceberg costs as $\tau^x_{nj} = (\text{Dist}^{\text{port}}_n)^{\xi_j}$, where $\text{Dist}^{\text{port}}_n$ is the distance between region n and the nearest port among the

[26] δ_{mt} absorb out $(1 - \sigma)\ln c_{njt} + (\sigma - 1)\delta\lambda^T_{njt} + \ln(\sum_m \tau_{nmj}P^{\sigma-1}_{mjt}E_{mjt} + \tau^x_{nj}D^x_{jt})$.

[27] If we had found that winners were more likely to receive subsidies, the sales estimates should have been mapped to the joint effects $(\sigma - 1)\ln(\frac{\eta}{1-s_{it}})$.

[28] 2.2 and 1.5 are calculated as $\eta = \exp(\frac{\sigma}{\sigma-1} \times 0.6)$ and $\delta = \frac{\sigma}{\sigma-1} \times 1.1$, where 0.6 is the average effect of the coefficients from the winners vs. losers research design and 1.1 is the average of the IV estimates of columns 2-8 in Panel B of Table 2.

[29] The value of 2 is also in line with the migration elasticity of 0.7 at the annual frequency by Choi (2022) based on the South Korean migration flows.

seven largest ports in South Korea. Any common components of the iceberg costs are not separately identifiable from D^x_{jt}, so we normalize $\tau^x_{nj} = 1$ for regions with ports. We take import tariffs directly from the data.

The remaining parameters We set the Pareto shape parameter θ to $1.06 \times (\sigma - 1)$ (Axtell, 2001; di Giovanni et al., 2011). We set M_{nj} to be proportional to the 1972 GDP share of each region and sector and set $\sum_{n,j} M_{nj} = 1$ (Chaney, 2008). The Cobb-Douglas shares of preference and production function, α_j, γ^k_j and γ^L_j, are taken from the IO tables.

5.2.2 Internal Calibration

Adoption subsidy The adoption subsidies are provided in $t = 2, 3$, corresponding to 1976 and 1980, and to firms in regions with at least one firm that ever received directed credit $\mathcal{N}^{\text{s}}$. 35 regions were included in $\mathcal{N}^{\text{s}}$. We assume the same subsidy level $\bar{s}$ across these regions and periods:

$$s_{njt} = \begin{cases} \bar{s} & \text{if} \quad t \in \{2, 3\}, \quad \forall n \in \mathcal{N}^{\text{s}}, \quad j = \{\text{heavy mfg.}\} \\ 0 & \text{otherwise.} \end{cases} \tag{5.3}$$

Adoption cost We parametrize adoption costs as a function of the distance to the nearest port: $F^T_{njt} = \varphi^T_{j0} + \varphi^T_{j1} \ln \text{Dist}^{\text{port}}_n$. φ^T_{j0} governs the common costs across regions and $\varphi^T_{j1} > 0$ captures the notion that if firms were located farther away from the ports, knowledge transfer becomes more costly.[30]

Constrained minimum distance We calibrate $\mathbf{\Theta}^{\text{M}}$, $\bar{s}$, and $\mathbf{\Psi}_t$ by minimizing the distance between the data moments and the model counterparts. Our calibration procedure requires moments from microdata and a set of cross-sectional aggregate variables in 1972, 1976, and 1980. Let $g(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) \equiv \bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)$ be the distance between a vector of the model moments $\bar{\mathbf{m}}$ and the data counterparts $\mathbf{m}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)$ and let $c(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) \equiv \mathbf{C}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{C}_t$ be the imposed constraints, where $\mathbf{C}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)$ and $\mathbf{C}_t$ are vectors of the model moments and data counterparts. We calibrate $\mathbf{\Theta}^{\text{M}}$, $\mathbf{\Psi}_t$, and $\bar{s}$ by solving the following constrained minimization problem:

$$\{\hat{\mathbf{\Theta}}^{\text{M}}, \hat{\bar{s}}\} \equiv \underset{\{\mathbf{\Theta}^{\text{M}}, \bar{s}\}}{\arg\min} \left\{ g(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)' g(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) \right\} \qquad \text{s.t.} \qquad c(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) = 0. \tag{5.4}$$

The moments are normalized to convert the difference between the model and the empirical moments into percentage deviation.

We choose the moments that are relevant and informative about the underlying parameters. We identify φ^T_{j0} and φ^T_{j1} using the average adopter shares across regions in 1972 and the estimates obtained from the PPML regression, where we regress the 1972 adopter shares on the log of the

[30] For example, training services provided by foreign engineers could have incurred higher costs for firms located farther away from ports due to higher mobility costs of these foreign engineers.

nearest distance to the port: $\lambda^T_{njt} = \exp(\beta_0 + \beta_1 \ln \mathrm{Dist}^{\mathrm{port}}_n) \times \epsilon_{njt}$. The estimated value of β^T_1 is $\hat{\beta}^T_1 = -0.35$, statistically significant under the 5%, implying that regions farther away from ports had lower adopter shares, consistent with Comin et al. (2012) who find technology diffuses slower to locations that are farther away from origins of new technologies. We run the same regression using the model-generated data and calibrate φ^T_{j1} to match $\hat{\beta}^T_1$.

We calibrate $\bar{s}$ by targeting the average adopter shares in 1976 and 1980. Conditional on the benefits from the adoption (direct and spillover effects) and F^T_{nj}, because $\bar{s}$ only enters in 1976 and 1980, the increases in the adopter shares in 1976 and 1980 relative to those in 1972 are informative about the subsidies.

With a lower κ, the cutoff adoption productivity becomes more likely to be above the Pareto upper bound, leading to zero adoption. Thus, we identify κ using the share of regions with positive adoption in 1972, 1976, and 1980. We calibrate F^x_j of the light and heavy manufacturing sectors to match the average exporter shares across regions and periods. Due to the lack of data on commodity sector firms, we set F^x_j of the commodity sector to be the same as that of the light manufacturing sector.

Conditional on $\mathbf{\Theta}^{\mathrm{M}}$ and $\bar{s}$, the constraints in Equation (5.4) identify $\mathbf{\Psi}_t$ based on the model-inversion logic (Allen and Arkolakis, 2014). We impose the constraints such that sectoral export and import shares, regional distribution of sectoral gross output, and regional population distribution of the model are exactly fitted to the data counterpart of 1972, 1976, and 1980. The number of the constraints is the same as the dimension of the fundamentals, so for any given $\mathbf{\Theta}^{\mathrm{M}}$ and $\bar{s}$, the fundamentals are exactly identified by these constraints and there exists a set of the fundamentals (up to normalization) that rationalizes the data.[31] D^x_{jt} and P^f_{jt} are identified by sectoral export intensities and import shares; $\phi^{\min}_{njt}$ by regional sectoral gross output distribution; and V_{nt} by population distribution.

Estimation results The model moments closely match their data counterparts, indicating that the calibrated model parameters successfully capture the patterns observed in the data (Table 5). The estimated subsidy rate is 0.08, which indicates that adopters are subsidized with 8% of input expenditures. In 1976 and 1980, the ratio between total subsidies provided to adopters and GDP is 0.5% and 1.2%, respectively. The adoption was more costly than exporting. The calibrated fixed adoption cost is about 71 times larger than the fixed export cost, calculated as the median of $c_{njt}F^T_{nj}/w_{nt}F^x_j$ across regions and periods.

[31] We only identify relative productivity differences across regions within sectors and periods and relative amenity differences. We normalize $\phi^{\min}_{njt}$ of the reference region to 1 for each sector and period and V_{nt} of the reference region to 1 for each period.

Table 5: Model Fit

Moment	Model	Data
Mean $\{\lambda^{x}_{njt}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$, light mfg.	0.23	0.24
Mean $\{\lambda^{x}_{njt}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$, heavy mfg.	0.16	0.13
Mean $\{\lambda^{T}_{nj,72}\}_{n\in\mathcal{N}}$	0.06	0.05
Mean $\{\lambda^{T}_{nj,76}\}_{n\in\mathcal{N}}$	0.11	0.07
Mean $\{\lambda^{T}_{nj,80}\}_{n\in\mathcal{N}}$	0.18	0.11
Shares of regions with adoption, 1972	0.33	0.24
Shares of regions with adoption, 1976	0.19	0.30
Shares of regions with adoption, 1980	0.46	0.36
PPML estimate, $\lambda^{T}_{nj,72}$ & dist. to port	-0.35	-0.36

Notes. This table presents the fit of the model.

6 Quantification of the Effects of the Big Push Policy

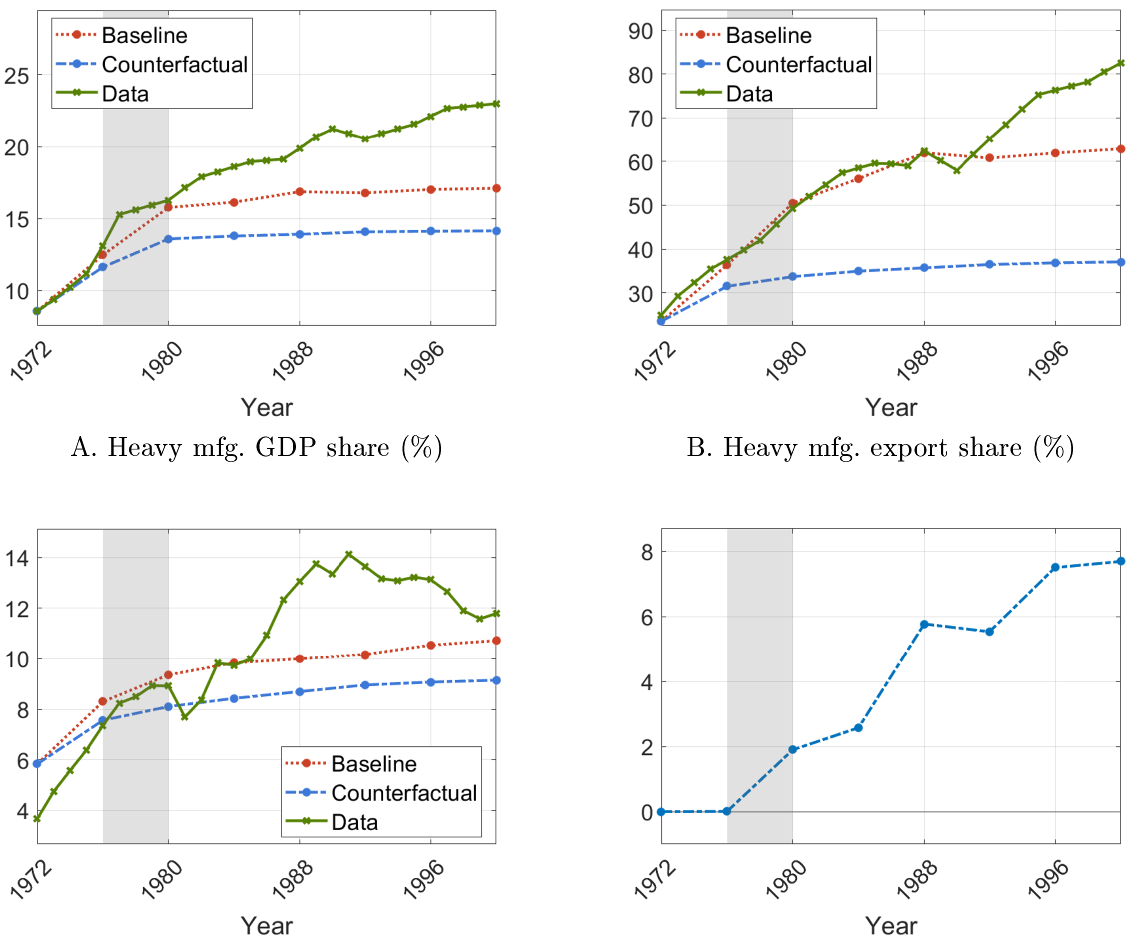
Using the calibrated model, we ask how the economy would have evolved differently, had the policy not been implemented. We compare the outcomes of the baseline economy in which the big push policy is implemented to those of the counterfactual economy in which the policy is not implemented.

Figure 5 reports this comparison. Had the policy not been implemented, the pattern of industrialization and its comparative advantage would have evolved differently because the counterfactual economy converges to an alternative less-industrialized steady state.[32] We compare the heavy manufacturing sector's shares of value added to GDP, shares of employment to total employment, and shares of exports to total exports. In this alternative steady state, the GDP share would have decreased by 3.1 percentage points, the export shares by 27.1 percentage points, and the employment share by 1.7 percentage points. Although we do not directly target the employment shares, the calibrated model approximates the evolution of the employment shares between 1972 and 1980 quite well, which is the non-targeted moment of the model. However, because we do not directly target data moments after 1980, our model does not explain the evolution of these outcomes after 1980 well. The aggregate welfare gains of the baseline are 8.2% permanently higher than the counterfactual once the economies reach steady states (Panel D). With the discount factor of 0.81, the discounted utility, $\sum_{t=1}^{\infty}\beta^{t-1}U_t^{agg}$, was 19.6% higher in the baseline.[33]

[32] Unlike the simple model that has a maximum of three steady states, the quantitative model potentially admits a larger number of steady states due to complex interaction across regions through costly trade and migration (Allen and Donaldson, 2020).

[33] The calibrated subsidies are not optimally designed, so there is room for welfare improvement. Analyzing the optimal subsidy in this economy is outside the purview of this paper. For the optimal policy, for example, see Bartelme

Figure 5. Aggregate Effects of the Big Push



A. Heavy mfg. GDP share (%)

B. Heavy mfg. export share (%)

C. Heavy mfg. emp. share (%)

D. Aggregate welfare gain (%)

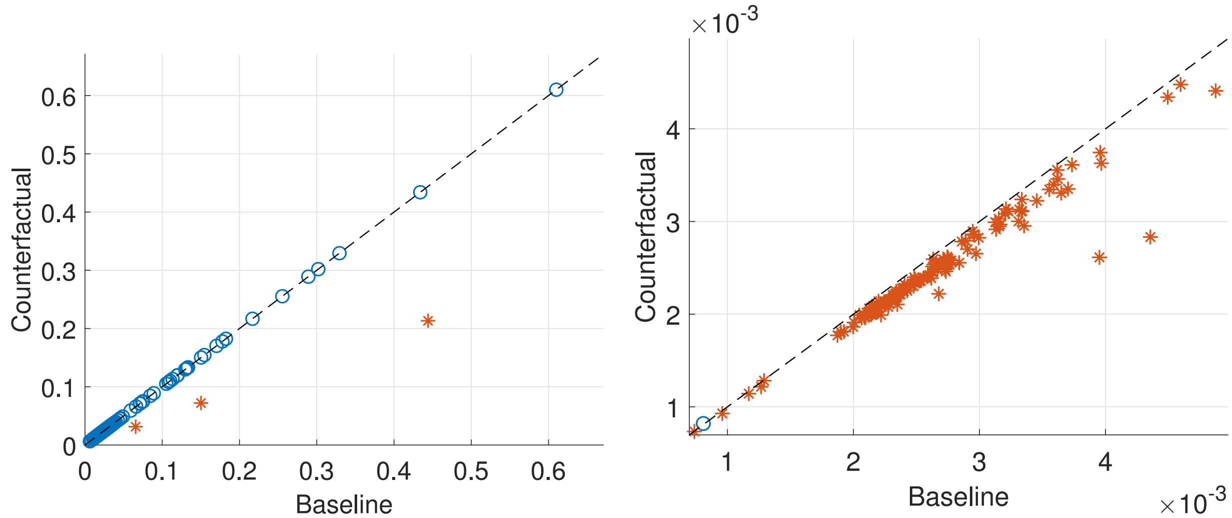
Notes. This figure plots the baseline and counterfactual results. The green solid line plots the data computed from the input-output tables. The red dotted and the blue dashed lines plot the outcomes of the baseline and the counterfactual economies. Panels A, B, and C illustrate the heavy manufacturing sector's GDP, export, and employment shares. Panel D illustrates the aggregate welfare gain in the baseline relative to the counterfactual economy.

Figure 6 illustrates region-level productivity and real income in the steady states. In Panel A, the x and y axes are each region's steady state productivity, $M_{nj}[\int z_{it}(\phi)^{\sigma-1} dG_{njt}(\phi)]^{1/(\sigma-1)}$, in the baseline and counterfactual economies.[34] Each dot represents each region and dots located below the 45-degree line, denoted as red stars, represent regions that had higher productivity in the baseline than the counterfactual. Only three regions gained higher productivity. This fact implies that

et al. (2020), Fajgelbaum and Gaubert (2020), and Lashkaripour and Lugovskyy (2020) in the static setting.

[34] Note that M_{nj} is not separately identifiable from $\phi^{\min}_{njt}$.

Figure 6. Local Productivity and Real Income



Steady state local

A. Productivity B. Real income

Notes. Panels A and B illustrate each region's productivity and real income under the baseline and counterfactual economies (x and y axes). Each dot represents each region and is colored red if a corresponding region had higher productivity and real income in the baseline economy.

the aggregate industrialization patterns documented in Figure 5 were driven by local productivity improvement of these three regions rather than the uniform improvement across the whole country. These uneven local changes are also consistent with Figure 2. In Panel B, the x and y axes refer to the steady state real income in the baseline and counterfactual economies. In the steady states, except for one region, all regions had higher real income in the baseline, because large productivity gains of the three regions were shared with households in other regions through trade and migration linkages.

International trade In this model, due to the Cobb-Douglas production and utility, consumers and firms spend a constant fraction of their total expenditures. Therefore, in the closed economy which is the limiting case of the open economy model that can be achieved by letting $P^f_{jt} \to \infty$ and $D^x_{jt} \to 0$, even if the big push induces the economy to reach an alternative steady state, the gross output shares would be constant across steady states despite different levels of the adoption. The increase in the gross output shares comes from the changes in South Korea's export patterns in the open economy. In the industrialized steady state, higher productivity in the heavy manufacturing sector increases its exports, which leads to higher gross output shares when compared to the less-industrialized steady state. Thus, in our model, the industrialization relates to changes in comparative

Table 6: Differences in the Steady States between the Baseline and the Counterfactual Economies

	Heavy mfg. shares (p.p.)		
	GDP	Export	Emp.
	(1)	(2)	(3)
Panel A. Baseline			
Baseline	3.1	27.1	1.7
Panel B. Scale complementarity			
Lower D_{jt}^F	0.3	0.8	0.7
No migration	3.1	27.1	1.7
No roundabout prod.	0.6	5.4	0.1
Panel C. Robustness. Different parameter values			
$\eta = 0.3$	2.1	19.9	1.6
$\delta = 2$	1.5	14.1	0.8
$\sigma = 5$	2.2	23.2	1.2

Notes. This table reports the quantitative results of the baseline and the counterfactual economies. Panel A reports the results under the baseline calibrated values. Panel B reports the results with lower foreign demand, when migration is not allowed, and when magnitude of IO linkages is reduced by 10% in 1976 and 1980. Panel C reports the results with different parameter values.

advantage induced by technology adoption.[35]

Scale complementarity The newly added elements of the quantitative model introduce additional complementarities between firm scale and the adoption because firms have larger profit gains from the adoption with a larger scale. The scale complementarities interact with the dynamic complementarity and potentially amplify the latter.[36] First, international trade makes firms scale larger through market size effects (Yeaple, 2005; Verhoogen, 2008; Lileeva and Trefler, 2010; Bustos, 2011). Second, forward and backward linkages due to roundabout production is another source of the scale complementarity (Krugman and Venables, 1995). Third, migration amplifies the scale complementarity in regions with higher adopter shares because these regions attract higher migration inflows, which lowers the labor costs of production.

[35] Previous papers in the trade literature have documented evolution of comparative advantage (e.g., Hanson et al., 2015; Levchenko and Zhang, 2016; Schetter, 2019; Atkin et al., 2021). See Arkolakis et al. (2019) for how immigration shapes comparative advantage; Cai et al. (2022) for knowledge diffusion; and Pellegrina and Sotelo (2021) for internal migration.

[36] Note that the scale complementarity differs from the dynamic complementarity. When fixed adoption costs are in units of labor, regardless of market size, the simple model does not feature dynamic complementarity and therefore multiple steady states. See Section C.3.

To examine quantitative aspects of interaction between these static complementarities and technology adoption, we conduct three additional exercises. In the first exercise, we assume a reduced level of foreign demand for the heavy manufacturing sector, maintaining it at the 1972 level in 1976 and 1980. In the second and third exercises, in 1976 and 1980, migration is prohibited and IO linkages of production are reduced by 10% ($\tilde{\gamma}_j^L = 1 - \sum_k \tilde{\gamma}_j^k$, $\tilde{\gamma}_j^k = 0.9 \times \gamma_j^k$, $\forall j, k \in \mathcal{J}$). In all exercises, the fundamentals and parameters differ from the baseline only for 1976 and 1980.

The results are presented in Panel B of Table 6. Lower foreign demand or reduced IO linkages lead to a smaller magnitude of the effects of the big push. These results highlight the complementarity between exporting and technology adoption, as well as the importance of inter-industry linkages, reminiscent of the points emphasized by Hirschman (1958) and more recently by Liu (2019). Migration play a quantitatively minor role, affecting only transitional dynamics but not the convergence to the steady states.

Robustness As discussed in Proposition 1(iv), the possibility of the big push and path dependence depends on the values of η and δ. In our analysis, we utilized their point estimates without accounting for the associated uncertainty. To assess the sensitivity of our results to this uncertainty, we consider the lower limit of the 95% confidence intervals of η and δ ($\eta = 0.3$ and $\delta = 2$) and repeat the counterfactual analysis using these alternative values. Furthermore, our estimates do not separately identify η or δ from σ. Therefore, we also consider alternative values of $\sigma = 5$, which gives lower values for η and δ. For each different set of values of the externally calibrated parameters, the other remaining parameters and the fundamentals are internally re-calibrated. Panel C of Table 6 reports the results. Even with these alternative parameter values, the big push still drives the economy towards different steady states through path dependence, although the magnitude of the quantitative results is reduced.

The assumptions of static technology adoption decisions and myopic migration The assumptions of myopic migration by households and static technology adoption decisions by firms make state variables $\{L_{nt}, M_{njt}^T\}$ backward-looking. This simplification allows us to preserve the rich spatial heterogeneity and connect the model to the empirical findings while facilitating computational implementation.[37] If adoption costs are sunk rather than fixed, adoption decisions become forward-looking and depend on the entire path of future wages and prices. Even with forward-looking decisions, the dynamic complementarity potentially generates multiple steady states, the setup studied by Alvarez et al. (2023). Because static equilibrium outcomes, such as employment, gross output, and export shares, are not affected by these simplifying assumptions, if we target the same path of state variables using such a forward-looking model with multiple steady states, our results do not change qualitatively. However, the calibrated values of the parameters and the counterfactual results from the forward-looking model would be quantitatively different.

[37] Desmet and Rossi-Hansberg (2014), Desmet et al. (2018), Nagy (2020), and Peters (2021) simplify forward-looking decisions of agents to make models more tractable while preserving rich spatial heterogeneity.

7 Conclusion

We empirically and quantitatively examine the effects of technology adoption on South Korea's late industrialization. We find that technology adoption not only brought benefits to adopting firms but also generated positive spillover effects for non-adopting firms at the local level. Furthermore, we find that the likelihood of firms adopting new technologies increased when more local firms engaged in adoption activities. Based on these findings, we build a dynamic spatial model to conduct a counterfactual analysis of the big push policy for the adoption implemented by the Korean government. Using the quantitative model calibrated to firm-level data and econometric estimates, we demonstrate that the big push policy could have had a long-lasting impact on the economy by propelling it towards a more industrialized steady state.

Our study highlights that knowledge flows from developed to developing countries can be an important driver of economic growth and the importance of addressing coordination failures to facilitate diffusion of advanced technologies into developing economies.

References

Acemoglu, Daron, "A Microfoundation for Social Increasing Returns in Human Capital Accumulation," *Quarterly Journal of Economics*, 1996, *111* (3), 779–804.

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

Adserà, Alícia and Debraj Ray, "History and Coordination Failure," *Journal of Economic Growth*, 1998, *3* (3), 267–276.

Alfaro-Ureña, Alonso, Isabela Manelici, and Jose P. Vasquez, "The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages," *Quarterly Journal of Economics*, 2022, *137* (3), 1495–1552.

Allen, Treb and Costas Arkolakis, "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 2014, *129* (2014), 1085–1139.

— **and Dave Donaldson**, "The Geography of Path Dependence in the Spatial Economy," *NBER Working Paper 28059*, 2020.

Alvarez, Fernando E., David Argente, Francesco Lippi, Esteban Méndez, and Diana Van Patten, "Strategic Complementarities in a Dynamic Model of Technology Adoption: P2P Digital Payments," *NBER Working Paper 31280*, 2023.

Amsden, Alice H., *Asia's Next Giant: South Korea and Late Industrialization*, Oxford University Press, 1989.

Arkolakis, Costas, Michael Peters, and Sun Kyoung Lee, "European Immigrants and the United States' Rise to the Technological Frontier," *Working Paper*, 2019.

Atkin, David, Arnaud Costinot, and Masao Fukui, "Globalization and the Ladder of Development: Pushed to the Top or Held at the Bottom?," *Working Paper*, 2021.

— **, Azam Chaudhry, Shamyla Chaudry, Amit K. Khandelwal, and Eric Verhoogen**, "Organizational Barriers to Technology Adoption: Evidence from Soccer-Ball Producers in Pakistan," *Quarterly Journal of Economics*, 2017, *132* (3), 1101–1164.

Axtell, Robert L., "Zipf Distribution of U.S. Firm Sizes," *Science*, 2001, *293* (5536), 1818–1820.

Azariadis, Costas and John Stachurski, "Poverty Traps," in Phillippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Amsterdam: Elsevier, 2005, chapter 5, pp. 295–384.

Bai, Jie, Panle Jia Barwick, Shengmao Cao, and Shanjun Li, "Quid Pro Quo, Knowledge Spillover, and Industrial Quality Upgrading: Evidence from the Chinese Auto Industry," *NBER Working Paper 27644*, 2020.

Banerjee, Abhijit V. and Esther Duflo, "Growth Theory through the Lens of Development Economics," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, 7 ed., Vol. 1, Amsterdam: Elsevier, 2005, chapter 7, pp. 473–552.

Bartelme, Dominick, Arnaud Costinot, Dave Donaldson, and Andres Rodriguez-Clare, "The Textbook Case for Industrial Policy: Theory Meets Data," *NBER Working Paper 26193*, 2020.

Bena, Jan, Miguel A. Ferreira, Pedro Matos, and Pedro Pires, "Are Foreign Investors Locusts? The Long-Term Effects of Foreign Institutional Ownership," *Journal of Financial Economics*, 2017, *126* (1), 122–146.

Bianchi, Nicola and Michela Giorcelli, "The Dynamics and Spillovers of Management Interventions: Evidence from the Training Within Industry Program," *Journal of Political Economy*, 2022, *130* (6), 1630–1675.

Blackwood, G. Jacob, Lucia S. Foster, Cheryl A. Grim, John Haltiwanger, and Zoltan Wolf, "Macro and Micro Dynamics of Productivity: From Devilish Details to Insights," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 142–172.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," *arXiv preprint arXiv:2108.12419*, 2023.

Broda, Christian and David E. Weinstein, "Globalization and the Gains from Variety," *Quarterly Journal of Economics*, 2006, *121* (2), 541–585.

Buera, Francisco J., Hugo Hopenhayn, Yongseok Shin, and Nicholas Trachter, "Big Push in Distorted Economies," *NBER Working Paper 28561*, 2021.

Bustos, Paula, "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms," *American Economic Review*, 2011, *101* (1), 304–340.

Cai, Jie, Nan Li, and Ana Maria Santacreu, "Knowledge Diffusion, Trade, and Innovation across Countries and Sectors," *American Economic Journal: Macroeconomics*, 2022, *14* (1), 104–145.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, "The Effect of Minimum Wages on Low-Wage Jobs," *The Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.

Chaney, Thomas, "Distorted Gravity: The Intensive and Extensive Margins of International Trade," *American Economic Review*, 2008, *98* (4), 1707–1721.

Choi, Jaedo, "Internal Migration, Sectoral Reallocation, and Large Devaluation," *Working Paper*, 2022.

— **and Andrei A. Levchenko**, "The Long-Term Effects of Industrial Policy," *NBER Working Paper 29263*, 2023.

— **and Younghun Shim**, "From Adoption to Innovation: State-Dependent Technology Policy in Developing Countries," *Working Paper*, 2022.

Ciccone, Antonio, "Input Chains and Industrialization," *Review of Economic Studies*, 2002, *69* (3), 565–587.

Comin, Diego, Mikhail Dmitriev, and Esteban Rossi-Hansberg, "The Spatial Diffusion of Technology," *NBER Working Paper 18534*, 2012.

Connolly, Michelle and Kei-Mu Yi, "How Much of South Korea's Growth Miracle Can Be Explained by Trade Policy?," *American Economic Journal: Macroeconomics*, 2015, *7* (4).

Costinot, Arnaud and Andrés Rodríguez-Clare, "Trade Theory with Numbers: Quantifying the Consequences of Globalization," in "Handbook of International Economics," Vol. 4 2014, pp. 197–261.

De Loecker, Jan, "Detecting Learning by Exporting," *American Economic Journal: Microeconomics*, 2013, *5* (3).

de Souza, Gustavo, "The Labor Market Consequences of Appropriate Technology," *Working Paper*, 2021.

Deshpande, Manasi and Yue Li, "Who is Screened Out? Application Costs and the Targeting of Disability Programs," *American Economic Journal: Economic Policy*, 2019, *11* (4), 213–248.

Desmet, Klaus and Esteban Rossi-Hansberg, "Spatial Development," *American Economic Review*, 2014, *104* (4), 1211–1243.

— **, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg**, "The Geography of Development," *Journal of Political Economy*, 2018, *126* (3), 903–983.

di Giovanni, Julian, Andrei A. Levchenko, and Romain Rancière, "Power Laws in Firm Size and Openness to Trade: Measurement and Implications," *Journal of International Economics*, 2011, *85* (1), 42–52.

Diodato, Dario, Ricardo Hausmann, and Ulrich Schetter, "A Simple Theory of Economic Development at the Extensive Industry Margin," *Working Paper*, 2022.

Donaldson, Dave and Richard Hornbeck, "Railroads and American Economic Growth: A "Market Access" Approach," *Quarterly Journal of Economics*, 2016, *131* (2), 799–858.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1749.

Enos, John L. and Woo-Hee Park, *The Adoption and Diffusion of Imported Technology: The Case of Korea*, Routledge, 1988.

Fajgelbaum, Pablo D. and Cecile Gaubert, "Optimal Spatial Policies, Geography, and Sorting," *Quarterly Journal of Economics*, 2020, *135* (2), 959–1036.

Giorcelli, Michela, "The Long-Term Effects of Management and Technology Transfers," *American Economic Review*, 2019, *109* (1), 121–152.

— **and Bo Li**, "Technology Transfer and Early Industrial Development: Evidence from the Sino-Soviet Alliance," *NBER Working Paper 29455*, 2021.

Goodman-Bacon, Andrew, "Difference-in-Differences with Variation in Treatment Timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti, "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings," *Journal of Political Economy*, 2010, *118* (3), 536–598.

Hanson, Gordon H., Nelson Lind, and Marc-Andreas Muendler, "The Dynamics of Comparative Advantage," *NBER Working Paper 21753*, 2015.

Hardy, Morgan and Jamie McCasland, "It Takes Two: Experimental Evidence on the Determinants of Technology Diffusion," *Journal of Development Economics*, 2021, *149*.

Helpman, Elhanan, Marc J. Melitz, and Yona Rubinstein, "Estimating Trade Flows: Trading Partners and Trading Volumes," *Quarterly Journal of Economics*, 2008, *123* (2), 441–487.

Hirschman, Albert O., *The Strategy of Economic Development*, Yale University Press, 1958.

Itskhoki, Oleg and Benjamin Moll, "Optimal Development Policies With Financial Frictions," *Econometrica*, 2019, *87* (1), 139–173.

Javorcik, Beata Smarzynska, "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? in Search of Spillovers through Backward Linkages," 2004.

Juhász, Réka, "Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade," *American Economic Review*, 2018, *108* (11), 3339–3376.

— **, Mara P. Squicciarini, and Nico Voigtländer**, "Technology Adoption and Productivity Growth: Evidence from Industrialization in France," *NBER Working Paper 27503*, 2020.

Keller, Wolfgang, "Geographic Localization of International Technology Diffusion," *American Economic Review*, 2002, *92* (1), 120–142.

Kim, Dae-Il and Robert H. Topel, "Labor Markets and Economic Growth: Lessons from Korea's Industrialization, 1970-1990," in "Differences and Changes in Wage Structures," Cambridge: National Bureau of Economic Research, 1995, pp. 227–264.

Kim, Linsu, *Imitation to Innovation: The Dynamics of Korea's Technological Learning*, Boston: Harvard Business School Press, 1997.

Kline, Patrick and Enrico Moretti, "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority," *Quarterly Journal of Economics*, 2014, *129* (1), 275–331.

Korea Industrial Technology Association, *Records of Technology Acquisition Contracts: 1962-1988*, Seoul: Korea Industrial Technology Association, [in Korean], 1988.

Krugman, Paul and Anthony J. Venables, "Globalization and the Inequality of Nations," *Quarterly Journal of Economics*, 1995, *110* (4), 857–880.

Lane, Nathan, "Manufacturing Revolutions Industrial Policy and Networks in South Korea," *Working Paper*, 2022.

Lashkaripour, Ahmad and Volodymyr Lugovskyy, "Scale Economies and the Structure of Trade and Industrial Policy," *Working Paper*, 2020.

Lee, Jong Wha, "Government Interventions and Productivity Growth," *Journal of Economic Growth*, 1996, *1* (3), 391–414.

Levchenko, Andrei A. and Jing Zhang, "The Evolution of Comparative Advantage: Measurement and Welfare Implications," *Journal of Monetary Economics*, 2016, *78*, 96–111.

Lileeva, Alla and Daniel Trefler, "Improved Access to Foreign Markets Raises Plant-Level Productivity. . .for Some Plants," *Quarterly Journal of Economics*, 2010, *125* (3), 1051–1099.

Liu, Ernest, "Industrial Policies in Production networks," *Quarterly Journal of Economics*, 2019, *134* (4), 1883–1948.

Lucas, Robert E., "Making a Miracle," *Econometrica*, 1993, *61* (2), 251–272.

— , "Life Earnings and Rural-Urban Migration," *Journal of Political Economy*, 2004, *112* (1), 29–59.

Luedde-Neurath, Richard, *Import Controls and Export-Oriented Development: A Reassessment of the South Korean Case*, Routledge, 1986.

Matsuyama, Kiminori, "Increasing Returns, Industrialization, and Indeterminacy of Equilibrium," *Quarterly Journal of Economics*, 1991, *106* (2), 617–650.

— , "Complementarities and Cumulative Processes in Models of Monopolistic Competition," *Journal of Economic Literature*, 1995, *33* (2), 701–729.

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

Ministry of Science and Technology, *Science and Technology Annual* 1972.

Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg, "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 2018, *108* (12), 3855–3890.

Moretti, Enrico, "The Effect of High-Tech Clusters on the Productivity of Top Inventors," *American Economic Review*, 2021, *111* (10), 3328–3375.

Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny, "Industrialization and the Big Push," *Journal of Political Economy*, 1989, *97* (5), 1003–1026.

Nagy, Dávid Krisztián, "Hinterlands, City Formation and Growth: Evidence from the U.S. Westward Expansion," *Working Paper*, 2020.

Nunn, Nathan, "Historical Development," in Philippe Aghion and Steven Dulauf, eds., *Handbook of Economic Growth*, Vol. 2, Elsevier, 2014, chapter 2, pp. 347–402.

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Parente, Stephen L. and Edward C. Prescott, *Barriers to Riches*, MIT Press, 2002.

Pellegrina, Heitor and Sebastian Sotelo, "Migration, Specialization, and Trade: Evidence from the Brazilian March to the West," *NBER Working Paper 28421*, 2021.

Peters, Michael, "Market Size and Spatial Growth - Evidence from Germany's Post-War Population Expulsions," *NBER Working Paper w29329*, 2021.

POSCO, *History of POSCO, 1968-2018 (in Korean)*, Pohang: POSCO, 2018.

Redding, Stephen, "The Low-Skill, Low-Quality Trap: Strategic Complementarities Between Human Capital and R&D," *Economic Journal*, 1996, *106* (435), 458–470.

Rodríguez-Clare, Andrés, "The Division of Labor and Economic Development," *Journal of Development Economics*, 1996, *49* (1), 3–32.

Rodrik, Dani, "Getting Interventions Right: How South Korea and Taiwan Grew Rich," *Economic Policy*, 1995, *20*, 53–107.

Rosenstein-Rodan, Paul N., "Problems of Industrialisation of Eastern and South-Eastern Europe," *Economic Journal*, 1943, *53*, 202–211.

Schetter, Ulrich, "A Structural Ranking of Economic Complexity," *Working Paper*, 2019.

Silva, J. M. C. Santos and Silvana Tenreyro, "The Log of Gravity," *Review of Economics and Statistics*, 2006, *88* (4), 641–658.

Sun, Liyang and Sarah Abraham, "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

Ventura, Jaume, "Growth and Interdependence," *Quarterly Journal of Economics*, 1997, *112* (1), 57–84.

Verhoogen, Eric A., "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector," *Quarterly Journal of Economics*, 2008, *123* (2), 489–530.

Vogel, Erza F., *The Four Little Dragons: The Spread of Industrialization in East Asia*, Harvard University Press, 1991.

Voth, Hans-Joachim, "Persistence: Myth and Mystery," in "The handbook of historical economics," Elsevier, 2021, pp. 243–267.

Westphal, Larry E, "Industrial Policy in an Export-Propelled Economy: Lessons from South Korea's Experience," *Journal of Economic Perspectives*, 1990, *4* (3), 41–59.

Yeaple, Stephen R., "A Simple Model of Firm Heterogeneity, International Trade, and Wages," *Journal of International Economics*, 2005, *65* (1), 1–20.

Young, Alwyn, "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience," *Quarterly Journal of Economics*, 1995, *110* (3), 641–680.

APPENDIX

Appendix A Data

Firm-level data From contract documents, we obtain three main pieces of information: names of domestic firms, names of foreign firms, and years contracts were made. We convert all monetary values into 2015 US dollars. The dataset covers firms with more than 50 employees. When a firm merged with another firm, we counted that as an exit. For firms with missing sales, we impute sales using assets. We convert the addresses of the location of production to the 2010 administrative divisions of South Korea. We classify firms into 10 manufacturing sectors, four of which are classified as heavy manufacturing, reported in Table A1. The numbers inside the parenthesis are ISIC Revision 3.1 codes.

Figure A1. Example. A Contract between Kolon and Mitsui Toatsu

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

Foreign firms' patent We match the USPTO with foreign firms in our dataset based on foreign firms' names. Then, we merge assignee IDs with the IDs from the Global Compustat (gvkey) based on the matching constructed by Bena et al. (2017). For foreign firms that have different assignee IDs but with the same Compustat ID, we give them a unique assignee ID and sum the numbers of

Table A1: Sector Classification

Aggregated Industry	Industry
(i) Chemicals, Petrochemicals, & Rubber, Plastic Products*	Coke oven products (231), Refined petroleum products (232) Basic chemicals (241), Other chemical products (242) Man-made fibres (243) except for pharmaceuticals and medicine chemicals (2423) Rubber products (251), Plastic products (252)
(ii) Electrical Equipment*	Office, accounting, & computing machinery (30) Electrical machinery and apparatus n.e.c. (31) Ratio, television and communication equipment and apparatus (32) Medical, precision, and optical instruments, watches and clocks (33)
(iii) Basic & Fabricated Metals*	Basic metals (27), Fabricated metals (28)
(iv) Machinery & Transport Equipment*	Machinery and equipment n.e.c. (29) Motor vehicles, trailers and semi trailers (34) Building and repairing of ships and boats (351) Railway and tramway locomotives and rolling stock (352) Aircraft and spacecraft (353), Transport equipment n.e.c. (359)
(v) Food, Beverages, & Tobacco	Food products and beverages (15), Tobacco products (16)
(vi) Textiles, Apparel, & Leather	Textiles (17), Apparel (18) Leather, luggage, handbags, saddlery, harness, and footwear (19)
(vii) Manufacturing n.e.c.	Manufacturing n.e.c. (369)
(viii) Wood, Paper, Printing, & Furniture	Wood and of products, cork (20), Paper and paper products (21) Publishing and printing (22), Furniture (361)
(ix) Pharmaceuticals & Medicine Chemicals	Pharmaceuticals and medicine chemicals (2423)
(x) Other Nonmetallic Mineral Products	Glass and glass products (261), On-metallic mineral products n.e.c. (269)

Notes. * denotes for heavy manufacturing sectors. The numbers inside parenthesis denote ISIC Rev 3.1 codes.

patents and citations up to the Compustat ID level.

Other regional and sectoral data The regional population data comes from the Population and Housing Census, the 2% random sample of the total population. We digitize import tariff data from Luedde-Neurath (1986) for 1968, 1974, 1976, 1978, 1980, and 1982. The tariffs are in the Customs Cooperation Council Nomenclature (CCCN). We convert CCCN to ISIC and then average the results across four-digit ISIC codes. For missing years, we impute values using the geometric average. We obtain IO tables from the Bank of Korea. We convert the codes of the IO tables into the ISIC codes.

Appendix B Empirics

B.1 An Example of POSCO

We provide an example involving POSCO to illustrate how technology adoption benefited firms through three channels documented by our empirical analysis. POSCO, currently one of the top five steel producers globally, was the first integrated steel mill in South Korea. Integrated steel mills play a crucial role in industrialization as they produce high-quality steel used as inputs in various manufacturing sectors.

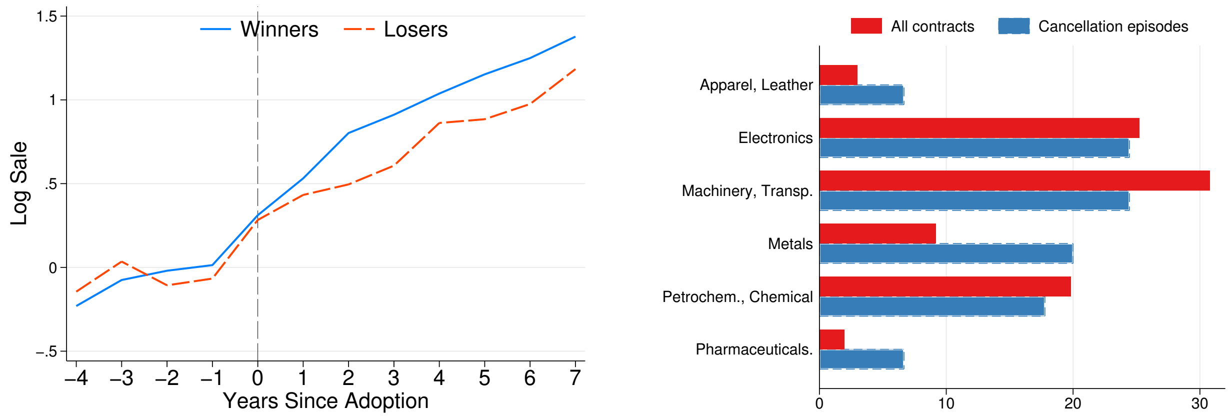
In 1968, POSCO initiated its first technology adoption contract with Nippon Steel Corporation (NSC), a Japanese company. This contract involved the transfer of blueprints, capital equipment, and the training of Korean engineers by NSC's engineers. From NSC's perspective, this contract was profitable, as the fixed fee paid by POSCO accounted for 20% of NSC's total annual exports in plant engineering. Additionally, the Korean government subsidized the costs of the capital equipment associated with the newly adopted technology by providing guaranteed foreign credit to POSCO. As a result of this contract, POSCO was able to commence production in 1973, exemplifying the direct effects of adoption on adopters, as discussed in our first finding.

Due to the local labor mobility of engineers across firms, the benefits of POSCO's newly acquired technology were not limited to its own operations. The engineers who received training from the Japanese engineers at POSCO gained new knowledge through learning by doing and reverse engineering. Subsequently, these engineers moved to smaller local mills or capital goods producers, diffusing their knowledge and improving the performance of these local firms. Local smaller-sized mills benefited from the acquisition of new skills brought by POSCO engineers. Additionally, local capital goods producers began manufacturing more advanced equipment, including water treatment and dust collection systems, as well as large magnetic cranes, which were previously imported in the early 1970s (Enos and Park, 1988, pp. 210-211). This knowledge diffusion through labor mobility aligns with our second finding on local spillovers.

Furthermore, the knowledge diffusion to local smaller-sized firms facilitated POSCO's adoption of more advanced technologies. In 1980, POSCO planned to adopt new technology related to the computerization of the production process, which involved substantial setup costs for installing new capital equipment and expanding existing plants. Despite no longer receiving government credit, POSCO decided to proceed with the adoption because the availability of cheaper domestic capital inputs, produced by local firms, reduced the setup costs (POSCO, 2018, pp.138-141). For the new expansion of production facilities in 1980, shares of expenditures on locally-produced capital equipment were 35%, which was 12% when they first adopted technology in 1968. This demonstrates the role of local firms in lowering the barriers to adoption, consistent with our third finding.

B.2 Additional Figures and Tables

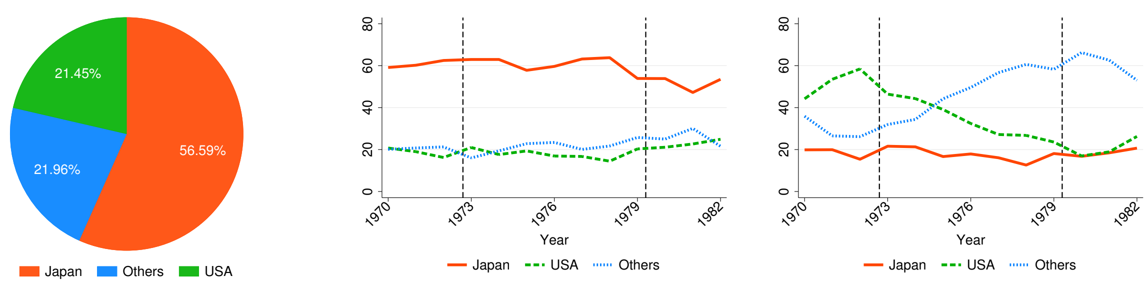
Figure B1. Raw Plots of the Data that Support the Identifying Assumption



A. Trends around the event B. Shares of contracts by sector (%)

Notes. Panel A displays the mean of log sales for winners and losers, normalized by the average before the event, respectively. Panel B illustrates the sectoral distribution of all contracts and cancellation episodes.

Figure B2. Technology Adoption, Export, and Import Shares by Country



Shares by country (%)

A. Technology adoption B. Export C. Import

Notes. This figure depicts the shares of technology adoption, export, and import in the heavy manufacturing sector across countries. The technology adoption shares represent the number of contracts from each country divided by the total number of contracts.

Table B1: Descriptive Statistics: Winners vs. Losers Design Samples from the Year of the Cancellation to 4 Years before the Cancellation

	Winner				Loser				t-Stat.	
	Mean	Med.	SD	Obs.	Mean	Med.	SD	Obs.	(Col. 1 - Col. 5)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Panel A. Domestic firm balance										
Log sales	17.56	17.40	2.0	319	17.97	18.06	1.82	194	0.99	[0.32]
Log emp.	6.98	7.09	1.23	237	7.05	7.21	1.49	153	0.04	[0.84]
Log fixed assets	16.82	16.74	2.18	319	16.98	16.96	2.23	194	0.10	[0.75]
Log assets	17.78	17.57	2.0	319	17.98	18.12	1.96	194	0.18	[0.67]
Panel B. Foreign firm patent activities										
Ihs # cum. patents	1.88	0	3.19	72	1.06	0	2.44	35	1.95	[0.17]
Ihs # cum. citations	2.0	0	3.4	72	1.14	0	2.63	35	1.86	[0.18]
$\mathbb{1}$[# cum. patents ≥ 0]	0.31	0	0.46	72	0.2	0	0.41	35	1.31	[0.26]
$\mathbb{1}$[# cum. citations ≥ 0]	0.31	0	0.46	72	0.2	0	0.41	35	1.31	[0.26]

Notes. Panel A reports the descriptive statistics of the winners vs. losers design samples from 4 years before the cancellations to the year of the cancellation. Panel B reports the descriptive statistics of patent activities by foreign firms matched with winners and losers. We report inverse hyperbolic sine transformation and a dummy of cumulative numbers of patents and citations. Column 9 reports the t-statistics of the mean difference between winners and losers with its p-value in brackets.

Table B2: Robustness. Covariate Balance Test

Var.	Log sale (N = 513)	Log emp. (N=390)	Log fixed assets (N=513)	Log assets (N=513)	Joint F-stat.
	(1)	(2)	(3)	(4)	(5)
Individually	-0.03 (0.03)	-0.01 (0.04)	-0.01 (0.03)	-0.01 (0.03)	NA
Jointly	-0.10 (0.07)	-0.02 (0.05)	-0.04 (0.09)	0.14 (0.14)	0.62 [0.65]

Notes. Standard errors in parenthesis are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the covariate balance test of the winners vs. losers design samples from 4 years before the cancellation to the year of the cancellation. In the first and second rows, we regress a dummy of winners on observable individually and jointly, respectively. For the joint specification, we report the F-statistics that test whether the observables are jointly zero.

Table B3: Robustness. Direct Effects on Adopters

Dep. Var.	Alternative TFP		Matching # = 2			Matching # = 4			Two-way clustering		
	Labor prod.	Export dummy	Sale	TFP^{rr}	Subsidy	Sale	TFP^{rr}	Subsidy	Sale	TFP^{rr}	Subsidy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
4 years before	–0.35	0.07	–0.15	–0.39	0.08	–0.08	–0.33	0.09	–0.08	–0.33	0.09
	(0.45)	(0.15)	(0.21)	(0.31)	(0.08)	(0.18)	(0.27)	(0.08)	(0.18)	(0.29)	(0.09)
3 years before	0.05	–0.00	0.05	–0.15	–0.00	0.03	–0.17	–0.01	0.03	–0.17	–0.01
	(0.32)	(0.10)	(0.17)	(0.23)	(0.09)	(0.14)	(0.21)	(0.07)	(0.13)	(0.22)	(0.09)
2 years before	0.05	–0.08	0.07	–0.08	0.03	0.15	–0.09	0.03	0.15	–0.09	0.03
	(0.29)	(0.10)	(0.14)	(0.20)	(0.08)	(0.13)	(0.18)	(0.08)	(0.13)	(0.18)	(0.08)
1 year before											
Year of event	0.04	–0.05	0.03	–0.04	0.03	0.01	–0.07	0.04	0.01	–0.07	0.04
	(0.15)	(0.08)	(0.12)	(0.12)	(0.09)	(0.11)	(0.12)	(0.09)	(0.11)	(0.13)	(0.09)
1 year after	0.58	0.16	0.67*	0.53	0.00	0.53	0.14	0.01	0.53*	0.14	0.01
	(0.46)	(0.19)	(0.36)	(0.36)	(0.10)	(0.32)	(0.39)	(0.09)	(0.29)	(0.19)	(0.10)
2 years after	1.15*	0.17	0.84***	0.72*	–0.05	0.96***	0.75*	–0.04	0.96***	0.75*	–0.04
	(0.63)	(0.19)	(0.28)	(0.37)	(0.12)	(0.35)	(0.45)	(0.11)	(0.33)	(0.43)	(0.11)
3 years after	0.49*	0.34*	0.71***	0.25	0.13	0.82**	0.15	0.09	0.82***	0.15	0.09
	(0.28)	(0.19)	(0.27)	(0.26)	(0.13)	(0.32)	(0.23)	(0.11)	(0.29)	(0.24)	(0.11)
4 years after	0.74**	0.09	1.00***	0.64**	–0.04	1.18***	0.59**	–0.04	1.18***	0.59*	–0.04
	(0.29)	(0.28)	(0.35)	(0.32)	(0.10)	(0.44)	(0.28)	(0.09)	(0.42)	(0.30)	(0.10)
5 years after	0.58*	–0.13	1.09**	0.59*	–0.04	1.28***	0.58*	–0.04	1.28**	0.58*	–0.04
	(0.34)	(0.19)	(0.41)	(0.35)	(0.09)	(0.47)	(0.31)	(0.09)	(0.47)	(0.34)	(0.09)
6 years after	1.30***	–0.18	1.02**	0.91***	–0.05	1.08**	0.86***	–0.05	1.08**	0.86**	–0.05
	(0.43)	(0.18)	(0.43)	(0.34)	(0.10)	(0.41)	(0.30)	(0.09)	(0.43)	(0.33)	(0.10)
7 years after	0.98**	–0.06	1.05**	0.78***	–0.05	1.11**	0.74***	–0.05	1.11**	0.74**	–0.05
	(0.41)	(0.28)	(0.45)	(0.29)	(0.10)	(0.43)	(0.26)	(0.09)	(0.42)	(0.28)	(0.10)
Match-firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Match-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# Cl. (Firm)	80	91	82	72	82	95	84	95	95	84	95
# Cl. (Match)									35	33	35
N	484	644	565	425	565	690	515	690	690	515	690

Notes. Standard errors in parenthesis are clustered at the firm level or two-way clustered at the firm and match levels in columns 1-8 or 9-11, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimated event study coefficients β_τ from winners vs. losers research design (Equation (3.1)). β_{-1} is normalized to zero. The dependent variables are log labor productivity, export dummy, log sales, TFP^{rr}, and a dummy of receiving a subsidy (credit). All specifications control for match-firm and match-year fixed effects. In columns 3-5 and 6-8, we consider alternative numbers of matched winners of 2 and 4, respectively.

Table B4: Robustness. Local Spillover. Placebo Test

Dep.	1970-1972 or 1971-1973					
	$\triangle \ln \text{Sales}_{it}$			$\triangle \mathbb{1}[\text{New Contract}_{i,t+1}]$		
	OLS	RF	IV	OLS	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle\text{Share}_{nj,t-2}$	-0.18		1.27	0.17		0.91
	(0.33)		(1.48)	(0.16)		(1.14)
$\text{IV}^{25\text{km}\geq}_{nj,t-2}$		0.37			0.25	
		(0.39)			(0.26)	
KP-F			8.26			7.86
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓
# Cl. (Region)	73	73	73	73	73	73
# Cl. (Group)	830	830	830	830	830	830
N	1004	1004	1004	1004	1004	1004

Notes. Standard errors two-way clustered at the levels of regions and business groups are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the OLS, reduced-form, and IV estimates of Equation (3.4). The adoption shares and IV are defined in Equations (3.3) and (3.5). In columns 1-3 and 4-6, dependent variables are changes in log sales or a dummy of making a new adoption contract between 1970 and 1972 or 1971 and 1973. In columns 1-3, we control for initial levels of dependent variables. All specifications include region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Paap F-statistics. In columns 1-3, we control for initial log sales in 1970 or 1971.

Table B5: Robustness. Functional Form. Local Spillover

Dep. $\triangle \ln \text{Sales}_{it}$ 1970-1972 or 1973-1980			
	(1)	(2)	(3)
$\triangle\text{Share}_{nj,t-2}$	3.29^{***}	2.68^{**}	2.85^{**}
	(1.14)	(1.23)	(1.19)
$\triangle\text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\text{Share}_{(-i)njt_0} \geq \text{p90}]$	-0.57		
	(2.89)		
$\triangle\text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\#\text{ firms}_{njt_0} \geq \text{p90}]$		-0.70	
		(2.04)	
$\triangle\text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\text{Sale}_{it_0} \geq \text{p90}]$			4.25
			(11.10)
SW-F, Share	8.93	37.45	40.61
SW-F, Interaction	42.96	15.61	60.31
Region FE	✓	✓	✓
Sector FE	✓	✓	✓
Sector-group FE	✓	✓	✓
# Cl. (Region)	78	78	78
# Cl. (Group)	1412	1412	1412
N	1644	1644	1644

Notes. Standard errors in parenthesis are two-way clustered at the levels of regions and business groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the IV estimates of Equation (3.4). In columns 1, 2, and 3, we include interaction terms between the adopter shares and dummies of whether the initial adopter shares, the initial number of firms, and the initial sales are above the 90th percentile, respectively. We instrument these terms with interaction terms between the IV in Equation (3.5) and the corresponding initial dummies. All specifications include region, sector, and sector-group fixed effects, and initial levels of dependent variables. SW-F is the Sanderson-Windmeijer F-statistics.

Table B6: Robustness. Local Spillover

Robustness.	Alternative outcomes/controls				Alternative samples				Alternative IV distances			
Dep.	△ Export dummy	△ Log labor prod.	△ ln Sales									
Sample	Baseline				Excl. firms affil. with business grp.	Excl. regions with heavy mfg. ind. complex	Single diff. 1973–1980	Full-sample	Baseline			
IV	$\text{IV}^{\geq 25\text{km}}_{inj,t-2}$			$\text{IV}^{\geq 25\text{km}}_{inj,t-3}$	$\text{IV}^{\geq 25\text{km}}_{inj,t-2}$				$\text{IV}^{\geq 0\text{km}}_{inj,t-2}$	$\text{IV}^{\geq 10\text{km}}_{inj,t-2}$	$\text{IV}^{\geq 50\text{km}}_{inj,t-2}$	$\text{IV}^{\geq 150\text{km}}_{inj,t-2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\triangle\text{Share}_{(-i)nj,t-2}$	1.03*	1.70**	2.88***		3.81***	3.69***	4.00***	3.93**	3.73***	4.06***	3.63***	3.75***
	(0.53)	(0.74)	(1.07)		(1.03)	(0.93)	(1.09)	(1.53)	(1.10)	(1.16)	(1.01)	(1.05)
$\triangle\text{Share}_{(-i)nj,t-3}$				4.88***								
				(1.73)								
KP-F	70.62	65.08	68.88	19.66	69.71	102.18	33.24	34.34	76.92	67.69	63.59	77.13
Region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Initial y_{it_0}	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
# Cl. (Region)	79	76	79	79	79	73	62	86	79	79	79	79
# Cl. (Group)	1294	744	1294	1294	1221	1241	724	1548	1294	1294	1294	1294
N	1492	826	1492	1492	1360	1422	734	1977	1492	1492	1492	1492

Notes. Standard errors in parenthesis are two-way clustered at the levels of regions and business groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the IV estimates of Equation (3.4). In column 1, 2, and 3-12, the dependent variables are changes in export dummies, log labor productivity, and log sales between 1972 and 1979 or 1973 and 1980, respectively. We consider the never-adopter sample in columns 1-4 and columns 9-12. We consider the alternative estimation sample that excludes firms affiliated with business groups in column 5; the sample that exclude firms in regions with the industrial complexes in column 6; a single difference between 1973 and 1980 in column 7; and the full-sample including both never- and ever-adopters in column 8. In columns 9-12, we consider alternative distances when constructing the IVs. All specifications include region, sector, and sector-group fixed effects, and initial levels of dependent variables. KP-F is the Kleibergen-Papp F-statistics.

Table B7: Robustness. Local Complementarity

Dep.	$\triangle\mathbb{1}[\text{New Contract}_{i,t+1}]$							
Sample	Baseline	Excl. firms affil. with business grp.	Excl. regions with heavy mfg. ind. complex	Single diff. 1973–1980	Baseline			
IV	$IV^{\geq 25km}_{inj,t-3}$	$IV^{\geq 25km}_{inj,t-2}$			$IV^{\geq 0km}_{inj,t-2}$	$IV^{\geq 10km}_{inj,t-2}$	$IV^{\geq 50km}_{inj,t-2}$	$IV^{\geq 150km}_{inj,t-2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\triangle\text{Share}_{(-i)nj,t-2}$		0.67**	0.71***	0.97***	0.78**	0.80**	0.68**	0.62**
		(0.27)	(0.26)	(0.31)	(0.37)	(0.38)	(0.27)	(0.27)
$\triangle\text{Share}_{(-i)nj,t-3}$	0.61*							
	(0.33)							
KP-F	7.70	34.86	52.50	19.08	36.51	31.80	34.51	42.95
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓	✓	✓
# Cl. (Region)	86	83	79	68	86	86	86	86
# Cl. (Group)	1548	1454	1468	923	1548	1548	1548	1548
N	1977	1701	1820	974	1977	1977	1977	1977

Notes. Standard errors in parenthesis are two-way clustered at the levels of regions and business groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the IV estimates of Equation (3.8). The dependent variables are changes of a dummy variable indicating whether firms made new adoption contracts between 1972 and 1979 or 1973 and 1980. We consider the full sample in column 1 and columns 5-8. We consider the alternative estimation sample that excludes firms affiliated with business groups in column 2; the sample that exclude firms in regions with the industrial complexes in column 3; and a single difference between 1973 and 1980 in column 4. In columns 5-8, we consider alternative distances when constructing the IVs. All specifications include region, sector, and sector-group fixed effects, and initial levels of dependent variables. KP-F is the Kleibergen-Papp F-statistics.

Appendix C Model

C.1 Derivation of Equation (4.3)

The adoption cutoff is

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

and the probability of adoption is $\lambda_t^T = (\bar{\phi}_t^T)^{-\theta}$, which gives $(\lambda_t^T)^{-\frac{1}{\theta}} = \bar{\phi}_t^T$.

We first show that $Q_t = A(\lambda_t^T) f(\lambda_{t-1}^T)$ and $\frac{w_t}{P_t} = \frac{1}{\mu} A(\lambda_t^T) f(\lambda_{t-1}^T)$, where

$$A(\lambda_t^T) = \left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\tilde{\theta}}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}}, \qquad \tilde{\theta} = \theta - (\sigma-1).$$

Because L_t is normalized to one, $\frac{L_t}{Q_t} = \frac{\int l(\omega)\mathrm{d}\omega}{Q_t} = \int \frac{y(\omega)}{Q}\frac{1}{z(\omega)}\mathrm{d}\omega = \int \frac{1}{z(\omega)}\big(\frac{p(\omega)}{P_t}\big)^{-\sigma}\mathrm{d}\omega$ holds, 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. Using that $p(\omega) = \frac{\mu w_t}{z(\omega)}$ and $P_t = \mu w_t[\int z(\omega)^{\sigma-1}\mathrm{d}\omega]^{\frac{1}{1-\sigma}}$, we obtain $Q_t = [\int z(\omega)^{\sigma-1}\mathrm{d}\omega]^{\frac{1}{\sigma-1}}$. From the assumption of Pareto distribution, we can further derive that

$$Q_t = \underbrace{\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\bar{\phi}_t^T)^{\tilde{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}} f(\lambda_{t-1}^T)}_{=[\int z(\omega)^{\sigma-1}d\omega]^{\frac{1}{\sigma-1}}} = \underbrace{\left[\frac{\theta}{\tilde{\theta}}\Big((\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\tilde{\theta}}{\theta}}+1\Big)\right]^{\frac{1}{\sigma-1}}}_{=A(\lambda_t^T)} f(\lambda_{t-1}^T), \tag{C.2}$$

where the second equality is derived from $(\lambda_t^T)^{-\frac{1}{\theta}} = \bar{\phi}_t^T$. Using that $[\int z(\omega)^{\sigma-1}d\omega]^{\frac{1}{\sigma-1}} = A(\lambda_t)f(\lambda_{t-1})$ and $P_t = \mu w_t[\int z(\omega)^{\sigma-1}\mathrm{d}\omega]^{\frac{1}{1-\sigma}}$, we obtain

$$\frac{w_t}{P_t} = \frac{w_t}{[\int(\mu w_t/z_{it}(\omega))^{1-\sigma}]^{\frac{1}{1-\sigma}}} = \frac{1}{\mu}A(\lambda_t^T)f(\lambda_{t-1}^T). \tag{C.3}$$

Substituting Equations (C.2) and (C.3) into Equation (C.1),

$$\lambda_t^T = \left(\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}A(\lambda_t^T)^{2-\sigma}f(\lambda_{t-1}^T)L_t\right)^{\frac{\theta}{\sigma-1}}. \tag{C.4}$$

Let $\hat{\lambda}_t^T$ be the solution of Equation (C.4). 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 Proofs of Propositions

Proposition 1(i) Because the left hand side of Equation (C.4) strictly increases in λ_t^T but the right hand side strictly decreases in λ_t^T due to Assumption 1(v), there exists a unique value of λ_t^T that satisfies this equation. If the obtained λ_t^T from this equation is greater than 1, $\lambda_t^T = 1$.

Proposition 1(ii) We apply the implicit function theorem. Let

$$G(\lambda_t^T;\eta,\delta,\lambda_{t-1}^T) = A(\lambda_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - (\lambda_t^T)^{\frac{\sigma-1}{\theta}}. \tag{C.5}$$

Taking the derivative of Equation (C.5) with respect to λ_t^T, we obtain

$$\frac{\partial G}{\partial \lambda_t^T} = \underbrace{\frac{2-\sigma}{\sigma-1}}_{<0} \times \underbrace{A(\lambda_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)(\lambda_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}}_{>0} - \underbrace{\frac{\sigma-1}{\theta}(\lambda_t^T)^{-\frac{\tilde{\theta}}{\theta}}}_{<0} < 0, \tag{C.6}$$

where the last inequality comes from the fact that $\frac{2-\sigma}{\sigma-1} < 0$ due to $\sigma > 3$ (Assumption 1). Taking the derivative with respect to λ_{t-1}^T,

$$\frac{\partial G}{\partial \lambda_{t-1}^T} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} f(\lambda_{t-1}^T)\delta > 0. \tag{C.7}$$

Applying the implicit function theorem and using the signs of Equations (C.6) and (C.7), we obtain $\frac{\partial \lambda_t^T}{\partial \lambda_{t-1}^T} = -\frac{\partial G/\partial \lambda_{t-1}^T}{\partial G/\partial \lambda_t^T} > 0$, which proves that λ_t^T strictly increases in λ_{t-1}^T.

Proposition 1(iii) Taking the derivative of Equation (C.5) with respect to η and δ, we obtain

$$\frac{\partial G}{\partial \eta} = A(\lambda_t^T)^{3-2\sigma} f(\lambda_{t-1}^T)\frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T}\frac{\theta}{\tilde{\theta}}\left[\frac{1}{\sigma-1}(\eta^{\sigma-1}-1)(\lambda_t^T)^{\frac{\theta}{\tilde{\theta}}}+1\right] > 0, \tag{C.8}$$

and

$$\frac{\partial G}{\partial \delta} = A(\lambda_t^T)^{2-\sigma}\frac{\eta^{\sigma-1}-1}{\sigma F^T} f(\lambda_{t-1}^T)\lambda_{t-1}^T > 0, \tag{C.9}$$

respectively. Applying the implicit function theorem and using the signs of Equations (C.6), (C.9), and (C.8), we obtain $\frac{\partial \lambda_t^T}{\partial \eta} = -\frac{\partial G/\partial \eta}{\partial G/\partial \lambda_t^T} > 0$ and $\frac{\partial \lambda_t^T}{\partial \delta} = -\frac{\partial G/\partial \delta}{\partial G/\partial \lambda_t^T} > 0$.

Proposition 1(iv) First, we show that λ_t^T is strictly convex in λ_{t-1}^T, $\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} > 0$. Applying the implicit function theorem,

$$\frac{\partial^2 \lambda_t^T}{\partial (\lambda_{t-1}^T)^2} = -\frac{1}{(\partial G/\partial \lambda_t^T)^3} \times \left[\frac{\partial G}{\partial \lambda_{t-1}^T}\left(\frac{\partial G}{\partial \lambda_t^T}\right)^2 - 2\frac{\partial^2 G}{\partial \lambda_t^T \partial \lambda_{t-1}^T}\frac{\partial G}{\partial \lambda_{t-1}^T}\frac{\partial G}{\partial \lambda_t^T} + \frac{\partial^2 G}{\partial (\lambda_t^T)^2}\left(\frac{\partial G}{\partial \lambda_{t-1}^T}\right)^2\right]. \tag{C.10}$$

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

$$\frac{\partial^2 G}{\partial(\lambda_{t-1}^T)^2} = A(\lambda_t^T)^{2-\sigma}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda_{t-1}^T)\delta^2 > 0. \tag{C.11}$$

$$\frac{\partial^2 G}{\partial\lambda_t^T\partial\lambda_{t-1}^T} = \frac{\partial^2 G}{\partial\lambda_{t-1}^T\partial\lambda_t^T} = \frac{2-\sigma}{\sigma-1}A(\lambda_t^T)^{3-2\sigma}\left[(\eta^{\sigma-1}-1)(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}\right] f(\lambda_{t-1}^T)\delta < 0. \tag{C.12}$$

$$\begin{aligned}\frac{\partial^2 G}{\partial(\lambda_t^T)^2} = &\frac{(2-\sigma)(3-\sigma)}{(\sigma-1)^2}A(\lambda_t^T)^{4-3\sigma}\left[\frac{\tilde{\theta}}{\theta}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}}(\eta^{\sigma-1}-1)\right]^2 f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} \\ &+ \frac{\sigma-2}{\theta}A(\lambda_t^T)^{3-2\sigma}(\lambda_t^T)^{-\frac{\sigma-1}{\theta}-1} f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)^2}{\sigma F^T} + \frac{\sigma-1}{\theta}\frac{\tilde{\theta}}{\theta}(\lambda_t^T)^{-\frac{\tilde{\theta}}{\theta}-1} > 0,\end{aligned} \tag{C.13}$$

where each term of the right hand side is positive due to the assumption $\sigma > 3$. Substituting Equations (C.6), (C.7), (C.11), (C.12), and (C.13) in Equation (C.10), we obtain $\frac{\partial^2\lambda_t^T}{\partial(\lambda_{t-1}^T)^2} > 0$, which proves strict convexity.

Because the intercept of λ_t^T-axis is always positive and λ_t^T is strictly increasing and strictly convex in λ_{t-1}^T, the locus defined by $(\lambda_{t-1}^T, \lambda_t^T)$ that satisfies Equation (4.3) can intersect with the 45-degree line two times at most. Note that the intercept is always positive because of the assumption of unbounded Pareto distribution which always guarantees a positive share of adopters.

Because λ_t^T strictly increases in δ, there exists $\underline{\delta}$ such that the 45-degree line and the short-run locus meet at $\lambda_{t-1}^T = 1$. In other words, holding other parameters constant including η, $\underline{\delta}$ satisfies $A(1;\eta)^{2-\sigma}f(1;\underline{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - 1 = 0$. Similarly, there exists $\underline{\eta}$ that satisfies $A(1;\underline{\eta})^{2-\sigma}f(1;\delta)\frac{(\underline{\eta}^{\sigma-1}-1)}{\sigma F^T} - 1 = 0$. Also, because λ_t^T is strictly convex in λ_{t-1}^T, there exists $\bar{\delta}$ and $\bar{\eta}$ such that the 45-degree line is tangent to the short-run locus implicitly defined by Equation (C.5). In other words, $\bar{\delta}$ and $\bar{\eta}$ satisfy $A(\lambda^T;\eta)^{2-\sigma}f(\lambda^T;\bar{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - \lambda^T = 0$ and $A(\lambda^T;\bar{\eta})^{2-\sigma}f(\lambda^T;\delta)\frac{(\bar{\eta}^{\sigma-1}-1)}{\sigma F^T} - \lambda^T = 0$, respectively, where $\lambda^T = \lambda_{t-1}^T = \lambda_t^T$.

For $\delta \in [0, \underline{\delta})$ or $\eta \in [0, \underline{\eta})$, the equilibrium share is always below one and the short-run locus implicitly defined by Equation(4.3) intersects with the 45-degree line only once. For $\delta \in (\bar{\delta}), 1]$ or $\eta \in (\bar{\eta}), 1]$, the short-run locus intersect with the 45-degree line at $\lambda^{T*} = \lambda_t^{T*} = \lambda_{t-1}^{T*} = 1$. For $\delta \in (\underline{\delta}, \bar{\delta})$ or $\eta \in (\underline{\eta}, \bar{\eta})$, the short-run locus and the 45-degree line intersect three times, leading to three multiple steady states. At the boundary values, the short-run locus intersects with the 45-degree line twice, leading to two multiple steady states.

Proposition 1(v) The welfare of household is $\frac{w_t+\Pi_t}{P_t}$ where Π_t are the aggregate profits summed across all firms in the economy. Using Equations (C.2) and (C.3) and the following expression

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

we can derive that the welfare can be expressed as $f(\lambda^T_{t-1})A(\lambda^T_t)$. The welfare in the steady state is $f(\lambda^{T*})A(\lambda^{T*})$, which strictly increases in λ^{T*}. Therefore, the equilibrium with a larger mass of adopters Pareto-dominates the equilibrium with a smaller share of adopters.

Proposition 2 Suppose an economy features multiple steady states S^{Pre}, S^{U}, and S^{Ind} and is initially stuck in the poverty trap.

First, consider input subsidies. Firms' costs of production are $(1 - s_{it})w_t l_{it}$ where $s_{it} = \bar{s}_t$ for $T_{it} = 1$ and 0 otherwise. $0 < \bar{s}_t < 1$ is the subsidy rate for adopters. Firm charges price $p(\omega) = \frac{\mu(1-s(\omega))w}{z(\omega)}$. The cutoff is

$$(\bar{\phi}^T_t)^{\sigma-1} = \frac{\sigma P_t F^T}{((\frac{\eta}{1-\bar{s}_t})^{\sigma-1} - 1)(\mu w_t)^{1-\sigma} f(\lambda^T_{t-1}) P^\sigma_t Q_t}.$$

$Q_t = A(\lambda^T_t)f(\lambda^T_{t-1})$ still holds with subsidies, but the expression for $\frac{w_t}{P_t}$ gets slightly modified

$$\frac{w_t}{P_t} = \frac{1}{\mu}\tilde{A}(\lambda^T_t, \bar{s}_t) f(\lambda^T_{t-1}), \quad \text{where} \quad \tilde{A}(\lambda^T_t, \bar{s}_t) = \left[\frac{\theta}{\tilde{\theta}}\left(\left(\left(\frac{\eta}{1-\bar{s}_t}\right)^{\sigma-1} - 1\right)(\lambda^T_t)^{\frac{\tilde{\theta}}{\theta}} + 1\right)\right]^{\frac{1}{\sigma-1}}.$$

The equilibrium share of adopters can be expressed as

$$\lambda^T_t = \left[\frac{\left(\frac{\eta}{1-\bar{s}_t}\right)^{\sigma-1} - 1}{\sigma F^T} A(\lambda^T_t)\tilde{A}(\lambda^T_t, \bar{s}_t)^{1-\sigma} f(\lambda^T_{t-1})\right]^{\frac{\theta}{\sigma-1}}. \tag{C.14}$$

Similarly with the subsidies to the fixed adoption costs $(1 - \bar{s}_t)P_t F^T$, the cutoff becomes

$$(\bar{\phi}^T_t)^{\sigma-1} = \frac{\sigma(1-\bar{s}_t)P_t F^T}{(\eta^{\sigma-1} - 1)(\mu w_t)^{1-\sigma} f(\lambda^T_{t-1}) P^\sigma_t Q_t}.$$

The equilibrium adopter shares are

$$\lambda^T_t = \left[\frac{\eta^{\sigma-1} - 1}{\sigma(1-\bar{s}_t)F^T} A(\lambda^T_t)^{2-\sigma} f(\lambda^T_{t-1})\right]^{\frac{\theta}{\sigma-1}}. \tag{C.15}$$

In the cases of both subsidies, the right hand side of both Equations (C.14) and (C.15) strictly increases in $\bar{s}_t$, and $\lim_{\bar{s}_t \to 0} \lambda^T_t \to 1$. Therefore, there exists $\underline{s}$ such that $\lambda^T_t = S^{\text{U}}$. For $\bar{s}_t > \underline{s}$, $\lambda^T_t > S^{\text{U}}$ and the economy starts to converge to S^{Ind}.

C.3 Source of Dynamic Complementarity

Let L_t denote the total labor endowment, which can be interpreted as the market size. We show that when fixed adoption costs are in units of labor, the model does not exhibit dynamic complementarity, regardless of L_t. When fixed adoption costs are in units of labor, the cutoff and equilibrium shares are determined as follows:

$$(\bar{\phi}_t^T)^{\sigma-1} = \frac{\sigma F^T}{(\eta^{\sigma-1}-1)\mu^{1-\sigma} f(\lambda_{t-1}^T)^{\sigma-1} P_t^\sigma Q_t}, \qquad \lambda_t^T = \Big(\frac{\mu(\eta^{\sigma-1}-1)L_t}{\sigma F^T} A(\lambda_t^T)^{1-\sigma}\Big)^{\frac{\theta}{\sigma-1}}.$$

Although a larger market size L_t increases the equilibrium share due to the scale complementarity, the share is uniquely determined regardless of the values of λ_{t-1}^T.

The reason why a larger market size does not result in dynamic complementarity is as follows. A higher value of λ_{t-1} increases overall productivity in t through spillover effects, which in turn, leads to higher demand for labor. This increased demand raises the equilibrium wage, resulting in higher $w_t F^T$. These increased costs exactly offset the larger incentives for the adoption induced by the spillover.

C.4 Possible Microfoundations for Adoption Spillovers

We provide two possible microfoundations for the spillovers. For both cases, we consider a simple closed economy setup with one sector and N regions. Goods are freely tradable and labor is freely mobile across regions, so wage and price indices are equalized across regions.

Local diffusion of knowledge A firm receives exogenous productivity $\tilde{\phi}_{it}$ and makes two static decisions each period, whether to adopt advanced foreign technology T_{it} and a level of innovation a_{it} as in Desmet and Rossi-Hansberg (2014). Their profit maximization problem is

$$\pi_{it} = \max_{T_{it}\in\{0,1\}, a_{it}\in[0,\infty)} \left\{ \frac{1}{\sigma}\left(\frac{\mu w_t}{\tilde{\eta}^{T_{it}} a_{it}^{\gamma_1} \tilde{\phi}_{it}}\right)^{1-\sigma} P_t^\sigma Q_t - T_{it} P_t F^T - w_t a_{it}^{\alpha_1} g(\lambda_{n,t-1}^T) P_t^\sigma Q_t \right\}, \tag{C.16}$$

where $\tilde{\eta}$ governs direct productivity gains from adoption, and $a_{it}^{\alpha_1} g(\lambda_{n,t-1}^T) P_t^\sigma Q_t$ 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 the cost of innovation is proportional to market size $P_t^\sigma Q_t$ and normalize $w_t = 1$ without loss of generality.

The positive externalities of adoption come from that the innovation costs are decreasing in the previous adopter shares $\partial g(\lambda_{n,t-1}^T)/\partial \lambda_{n,t-1}^T < 0$, which captures that with higher adopter shares, other local firms are more likely to learn new ideas from these adopters and use this knowledge for their own innovation in a reduced-form. We impose that $\tilde{\alpha} = \alpha_1 - \gamma_1(\sigma-1) > 0$ holds, which guarantees the second-order condition of a firm's maximization problem.

Using the first-order condition, a firm's optimal level of a_{it} is characterized as

$$a_{it}^* = (\frac{\gamma_1}{\alpha_1}\mu^{-\sigma})^{\frac{1}{\tilde{\alpha}}} g(\lambda_{n,t-1}^T)^{-\frac{1}{\tilde{\alpha}}} (\tilde{\eta}^{T_{it}} \tilde{\phi}_{it})^{\frac{\sigma-1}{\tilde{\alpha}}}.$$

Because $-1/\tilde{\alpha} > 0$ and $(\sigma-1)/\tilde{\alpha} > 0$, a_{it}^* increases in $\lambda_{n,t-1}^T$, T_{it}, and $\tilde{\phi}_{it}$. Substituting a_{it}^* into

Equation (C.16), a firm's maximization problem can be re-written as:

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} \left\{ \bar{C} \left(\frac{1}{g(\lambda^T_{n,t-1})^{-\frac{\gamma_1}{\tilde{\alpha}}} (\tilde{\eta}^{\frac{\alpha_1}{\tilde{\alpha}}})^{T_{it}} (\tilde{\phi}_{it})^{\frac{\alpha_1}{\tilde{\alpha}}}} \right)^{1-\sigma} P_t^{\sigma} Q_t - T_{it} P_t F^T \right\},$$

where $\bar{C}$ is a collection of model parameters. $g(\lambda^T_{n,t-1})^{-\frac{1}{\tilde{\alpha}}}$ can be mapped to $f(\lambda^T_{n,t-1})$, $(\tilde{\phi}_{it})^{\frac{\alpha_1}{\tilde{\alpha}}}$ to ϕ_{it}, and $\tilde{\eta}^{\frac{\gamma_1}{\alpha_1 - 1 - \gamma_1(\sigma-1)}}$ to η.

Learning externalities and labor mobility In each region, there is a unit measure of engineers and owners of firms, both of which are immobile across regions. Engineers live in two periods, child and adult. Once they become adults in the second period, they give birth to a child. They only consume and work in their adulthood. Engineers who work in firms that adopted technologies pass their knowledge to their children. This learning from parents increases the engineering skills of children when they grow up, which increases their skills by $\gamma_1 > 1$. If parents do not work in firms with foreign technology, their children's engineering skills are 1.

Engineers and owners are randomly matched one to one (Acemoglu, 1996). After a match, production happens and they jointly maximize profits. The profits this match generates are divided among engineers and owners based on Nash bargaining. Managers take a proportion of $\tilde{\beta}$. Because owners make adoption decisions before a match happens, they must make these decisions based on anticipated profits. Because of the random matching process, owners are matched with high- and low-skilled engineers with a probability of $\lambda^T_{n,t-1}$ and $1 - \lambda^T_{n,t-1}$, respectively.

A firm's maximization problem is

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} (1-\tilde{\beta}) \left\{ \lambda^T_{n,t-1} \left[\frac{1}{\sigma} \left(\frac{\mu w_t}{\eta^{T_{it}} \gamma_1 \phi_{it}} \right)^{1-\sigma} P_t^{\sigma} Q_t \right] + (1-\lambda^T_{n,t-1}) \left[\frac{1}{\sigma} \left(\frac{\mu w_t}{\eta^{T_{it}} \phi_{it}} \right)^{1-\sigma} P_t^{\sigma} Q_t \right] - P_t F^T T_{it} \right\}.$$

This can be re-written as

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} (1-\tilde{\beta}) \left\{ \frac{1}{\sigma} \left(\frac{\mu w_t}{\tilde{f}(\lambda^T_{n,t-1}) \eta^{T_{it}} \phi_{it}} \right)^{1-\sigma} P_t^{\sigma} Q_t - P_t F^T T_{it} \right\},$$

where $\tilde{f}(\lambda^T_{n,t-1}) = [\lambda^T_{n,t-1}(\gamma_1^{\sigma-1} - 1) + 1]^{\frac{1}{\sigma-1}}$.

Appendix D Quantitative Model

Sector A final goods producer aggregate varieties using a CES aggregator:

$$Q_{njt} = \left[\sum_m \int_{\omega\in\Omega_{mj}} (q_{njt}(\omega))^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega + (q^f_{njt})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where $q_{njt}(\omega)$ and q^f_{njt} are the quantities demanded of a variety produced by a domestic and a foreign firms, respectively. The exact price index is given by Equation (5.1)

Firm With the CRS Cobb-Douglas production, unit costs of input bundles are

$$c_{njt} = \Big(\frac{w_{nt}}{\gamma_j^L}\Big)^{\gamma_j^L} \prod_k \Big(\frac{P_{nkt}}{\gamma_j^k}\Big)^{\gamma_j^k}.$$

Firm i's quantities demanded from region m are Foreign are $q_{inmjt} = (p_{inmjt})^{-\sigma} P_{mjt}^{\sigma-1} E_{mjt}$ and $q^x_{injt} = (p^x_{injt})^{-\sigma} D^x_{jt}$. A firm optimally charges a constant markup over its marginal cost. Thus, the prices charged by firm i in region n of sector j charged to buyers in region m are $p_{inmjt} = \mu\tau_{nmj}c_{njt}/z_{it}$ and export prices are $p^x_{injt} = \mu\tau^x_{nj}c_{njt}/z_{it}$.

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

$$\begin{aligned}
\pi_{it} = \pi(\phi_{it}) &= \max_{x_{it}, T_{it}\in\{0,1\}} \{\pi(T_{it}, x_{it}; \phi_{it})\} \\
&= \max_{x_{it}, T_{it}\in\{0,1\}} \Bigg\{ \underbrace{\sum_m \Bigg[\frac{1}{\sigma}\Bigg(\mu\frac{\tau_{nmj}(1-s_{njt})^{T_{it}}c_{njt}}{\phi_{it}\eta^{T_{it}} f(\lambda^T_{nj,t-1})}\Bigg)^{1-\sigma} P_{mjt}^{\sigma-1}E_{mjt}\Bigg]}_{:=\pi^{\mathrm{d}}(T_{it};\phi_{it}) = \sum_m \pi^m(T_{it};\phi_{it})} \\
&\qquad + x_{it}\Bigg[\underbrace{\frac{1}{\sigma}\Bigg(\mu\frac{\tau^x_{nj}(1-s_{njt})^{T_{it}}c_{njt}}{\phi_{it}\eta^{T_{it}} f(\lambda^T_{nj,t-1})}\Bigg)^{1-\sigma} D^x_{jt}}_{:=\pi^x(T_{it};\phi_{it})} - w_{nt}F^x_j\Bigg] - T_{it}c_{njt}F^T_{nj}\Bigg\},
\end{aligned} \tag{D.1}$$

where x_{it} and T_{it} are binary export and adoption decisions, E_{mjt} are region m's total expenditures on sector j goods, D^x_{jt} are exogenous foreign demands, and F^x_j are fixed export costs in units of labor. $\pi^m(T_{it};\phi_{it})$ are operating profits conditional on adoption status obtained from region m, and $\pi^{\mathrm{d}}(T_{it};\phi_{it}) = \sum_m \pi^m(T_{it};\phi_{it})$ are the sum of all operating profits from domestic regions. $\pi^x(T_{it};\phi_{it})$ are operating profits in foreign markets conditional on adoption status.

Firms' adoption and export decisions are characterized by the cutoff productivities. Only firms with productivity above these cutoffs participate in adoption and exporting. To avoid a taxonomic presentation, we only consider a case in which fixed adoption costs are high enough so that the adoption cutoff is higher than the export cutoff in all regions. In the quantitative analysis, we allow for other possibilities.

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

$$\bar{\phi}^x_{njt} = \frac{\mu c_{njt}(\sigma w_{nt}F^x_j)^{\frac{1}{\sigma-1}}}{f(\lambda^T_{nj,t-1})\big((\tau^x_{nj})^{1-\sigma}D^x_{jt}\big)^{\frac{1}{\sigma-1}}}. \tag{D.2}$$

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

$$\bar{\phi}^T_{njt} = \frac{\mu c_{njt}(\sigma c_{njt} F^T_{nj})^{\frac{1}{\sigma-1}}}{\left(\left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1} - 1\right)^{\frac{1}{\sigma-1}} f(\lambda^T_{nj,t-1})\left(\sum_m \tau^{1-\sigma}_{nmj} P^{\sigma-1}_{mjt} E_{mjt} + (\tau^x_{nj})^{1-\sigma} D^x_{jt}\right)^{\frac{1}{\sigma-1}}}. \tag{D.3}$$

A share of adopters is expressed as

$$\lambda^T_{njt} = 1 - G_{njt}(\bar{\phi}^T_{njt}) = \begin{cases} 1 & \text{if} \quad \bar{\phi}^T_{njt} \leq \phi^{\min}_{njt} \\ \frac{(\bar{\phi}^T_{njt}/\phi^{\min}_{njt})^{-\theta} - \kappa^{-\theta}}{1-\kappa^{-\theta}} & \text{if} \quad \phi^{\min}_{njt} < \bar{\phi}^T_{njt} \leq \kappa\phi^{\min}_{njt} \\ 0 & \text{if} \quad \kappa\phi^{\min}_{njt} \leq \bar{\phi}^T_{njt}, \end{cases} \tag{D.4}$$

where $G_{njt}(\phi)$ is productivity distribution of nj in t. A mass of adopters is $M^T_{njt} = M_{nj}\lambda^T_{njt}$. Similarly, a share of exporters is $\lambda^x_{njt} = 1 - G_{njt}(\bar{\phi}^x_{njt})$ and a mass of exporters is $M^x_{njt} = M_{nj}\lambda^x_{njt}$.

Region-sector variables We define the region-sector level average firm productivity inclusive of subsidies as

$$\begin{aligned} \bar{\phi}^{\text{avg}}_{njt} &= f(\lambda^T_{nj,t-1})\left[\int_{\phi^{\min}_{njt}}^{\bar{\phi}^T_{njt}} \phi^{\sigma-1}_{it} dG_{njt}(\phi_{it}) + \int_{\bar{\phi}^T_{njt}}^{\kappa\phi^{\min}_{njt}} \left(\frac{\eta}{1-s_{njt}}\phi_{it}\right)^{\sigma-1} dG_{njt}(\phi_{it})\right]^{\frac{1}{\sigma-1}} \\ &= \frac{\theta f(\lambda^T_{njt-1})(\phi^{\min}_{njt})^{\frac{\theta}{\sigma-1}}}{\tilde{\theta}(1-\kappa^{-\theta})}\left\{\left((\phi^{\min}_{njt})^{-\tilde{\theta}} - (\bar{\phi}^T_{njt})^{-\tilde{\theta}}\right) + \left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1}\left((\bar{\phi}^T_{njt})^{-\tilde{\theta}} - (\kappa\phi^{\min}_{njt})^{-\tilde{\theta}}\right)\right\}, \end{aligned}$$

which can be expressed as a function of $\bar{\phi}^T_{njt}$. $\bar{\phi}^{\text{avg}}_{njt}$ captures the average cost advantage of sector j firms in region n. $\bar{\phi}^{\text{avg}}_{njt}$ decreases in $\bar{\phi}^T_{njt}$ but increase in s_{njt} and $\lambda^T_{nj,t-1}$. The average productivity for exporters can be expressed similarly:

$$\bar{\phi}^{\text{avg,x}}_{njt} = \frac{\theta f(\lambda^T_{njt-1})(\phi^{\min}_{njt})^{\frac{\theta}{\sigma-1}}}{\tilde{\theta}(1-\kappa^{-\theta})}\left\{\left((\bar{\phi}^{\text{x}}_{njt})^{-\tilde{\theta}} - (\bar{\phi}^T_{njt})^{-\tilde{\theta}}\right) + \left(\frac{\eta}{1-s_{njt}}\right)^{\sigma-1}\left((\bar{\phi}^T_{njt})^{-\tilde{\theta}} - (\kappa\phi^{\min}_{njt})^{-\tilde{\theta}}\right)\right\}.$$

Aggregate variables can be expressed as a function of $\bar{\phi}^{\text{avg}}_{njt}$ and $\bar{\phi}^{\text{avg,x}}_{njt}$. The price index is

$$P^{1-\sigma}_{njt} = \sum_m \left[M_{mj}\left(\frac{\mu\tau_{mnj}c_{mjt}}{\bar{\phi}^{\text{avg}}_{mjt}}\right)^{1-\sigma}\right] + (\tau^x_{nj}(1+t_{jt})P^f_{jt})^{1-\sigma}.$$

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

$$\pi_{mnjt} = \left(\frac{\tau_{mnj}c_{mjt}/\bar{\phi}^{\text{avg}}_{mjt}}{P_{njt}}\right)^{1-\sigma} \qquad \text{and} \qquad \pi^f_{njt} = \left(\frac{\tau^x_{nj}(1+t_{jt})P^f_{jt}}{P_{njt}}\right)^{1-\sigma}.$$

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

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

The total regional gross output is $R_{njt} = R^{\mathrm{d}}_{njt} + R^{x}_{njt}$.

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

$$w_{nt}L_{nt} = \left[\sum_{j}\gamma^{L}_{j}\left(\frac{1}{\mu}R_{njt} + M^{T}_{njt}c_{njt}F^{T}_{nj}\right) + M^{x}_{njt}w_{nt}F^{x}_{j}\right], \tag{D.5}$$

where the right-hand side is the sum of labor used for production, fixed adoption costs, and fixed export costs. Goods market clearing implies

$$R^{\mathrm{d}}_{njt} = \sum_{m}\pi_{nmjt}(\alpha_j w_{nt}L_{nt} + \gamma^{j}_{k}\frac{1}{\mu}R_{nkt} + \gamma^{j}_{k}M^{T}_{njt}c_{njt}F^{T}_{nj}). \tag{D.6}$$

The government budget is balanced each period:

$$\sum_{n}\sum_{j}\frac{t_{jt}}{1+t_{jt}}\pi^{f}_{njt}E_{njt} + \tau^{w}_{t}\sum_{n}w_{nt}L_{nt} = \sum_{n}\sum_{j}\left[\frac{s_{njt}}{1-s_{njt}}M_{nj}\int_{\bar{\phi}^{T}_{njt}}^{\kappa\phi^{\min}_{njt}}\frac{1}{\mu}r(\phi_{it})dG_{njt}(\phi)\right], \tag{D.7}$$

where the left-hand side is sum of revenues from tariffs and labor tax.

Equilibrium We formally define the equilibrium as follows.

Definition 1. *Given initial conditions $\{\lambda^{T}_{njt_0}, L_{nt_0}\}$ and a path of the fundamentals $\{\phi^{min}_{njt}, V_{nt}, P^{f}_{jt}, D^{x}_{jt}\}$, tariffs $\{t_{jt}\}$, subsidies $\{s_{njt}\}$, and, an 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 adopter shares $\{\lambda^{T}_{njt}\}$ such that for each period t, (i) firms maximize profits; (ii) households maximize utility; (iii) labor markets clear; (iv) goods markets clear; (v) trade is balanced, and (vi) the government budget is balanced; and (vii) firms' adoption and households' migration decisions endogenously determine the path of state variables λ_{njt} and L_{nt}, respectively.*

Appendix E Quantification

E.1 Calibration Procedure

Data inputs The quantitative exercises require the following data inputs:

1. Initial adopter shares $\{\lambda^{T}_{nj,68}\}_{n\in\mathcal{N},j\in\mathcal{J}^{T}}$ and population $\{L^{\mathrm{Data}}_{n,68}\}_{n\in\mathcal{N}}$ in 1968
2. Region-sector gross output $\{R^{\mathrm{Data}}_{njt}\}_{n\in\mathcal{N},j\in\mathcal{J},t\in\{72,76,80\}}$
3. Population $\{L^{\mathrm{Data}}_{nt}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$
4. Sectoral exports and import shares $\{\mathrm{EX}^{\mathrm{Data}}_{jt}, \pi^{f,\mathrm{Data}}_{jt}\}_{j\in\mathcal{J},t\in\{72,76,80\}}$

5. Import tariffs $\{t_{jt}\}_{j\in\mathcal{J},t\in\{72,76,80\}}$

Algorithm Taking the values of $\mathbf{\Theta}^{\mathrm{E}}$ and data inputs as given, we obtain the values of $\mathbf{\Theta}^{\mathrm{M}}$, $\bar{s}$, and $\mathbf{\Psi}_t$ using the following calibration algorithm:

1. Guess parameters.
2. Guess fundamentals $\{c_{fj}, D_{fj}\}_{j\in\mathcal{J}}$, $\{V_{nt}\}_{n\in\mathcal{N}}$, and $\{\phi_{nj}^{\min}\}_{n\in\mathcal{N},j\in\mathcal{J}}$.
3. Given parameters $\{\mathbf{\Theta}^{\mathrm{M}}, \bar{s}\}$, we solve the model and update the fundamentals $\mathbf{\Psi}_t$ for each period. Then, we fit region- and sector-level aggregate outcomes to the data counterparts. This step corresponds to the constraints of Equation (5.4).
   (a) Update $\{D_{jt}^{f'}\}$ by fitting the export intensities of the model to those in the data.
   (b) Update $\{P_{jt}^{F'}\}$ by fitting the import shares of the model to those in the data.
   (c) Update $\{V'_{nt}\}$ until the population outcome of the model matches the actual distribution of the population. Since only relative levels of $\{V'_{nt}\}$ are identified from the above equation, we normalize the value of the amenity of the reference region n_0 to be 1 for each period.
   (d) Update $\{\phi_{nj}^{min'}\}$ until the shares of regional gross output exactly match the data counterparts $GO_{njt}^{\mathrm{Data}}/\sum_{m,k} GO_{mkt}^{\mathrm{Data}}$. Within each sector, $GO_{njt}^{\mathrm{Data}}/\sum_{m,k} GO_{mkt}^{\mathrm{Data}}$ only identifies the relative levels, so we normalize the Pareto lower bound parameter of the reference region to 1 for each sector and period.
4. After updating the geographic fundamentals, given values of parameters and subsidies, we evaluate the objective function.
5. We iterate steps 1-4 until we find values of $\{\hat{\mathbf{\Theta}}^{\mathrm{M}}, \hat{\mathbf{s}}_t\}$ that minimize the objective function.