Technology Adoption and Late Industrialization*

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Abstract

We study how foreign technology adoption drives late industrialization in developing countries. Leveraging unique historical data from 1970s South Korea, we provide causal evidence that technology adoption improved the performance of adopters and generated positive local spillovers to non-adopters. Also, higher levels of local adoption increased the likelihood of new technology adoption, revealing evidence of local complementarity. We develop a dynamic spatial general equilibrium model consistent with these findings. Because of 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 yielded permanent effects by shifting the economy toward a more industrialized steady state, characterized by higher heavy manufacturing sector's GDP and export shares, and increased adoption levels.

Keywords: technology adoption, industrialization, big push, complementarity, knowledge spillover
JEL Codes: O14, O33, O53, R12

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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 shifted from agriculture to manufacturing, while many others remained stagnant. These latecomers achieved industrialization by adopting foreign technology rather than developing their own technology, a feature labeled as late industrialization (Amsden, 1989).[1] Although the experience of these countries is suggestive evidence of the importance of technology adoption for economic development (e.g., Parente and Prescott, 2002), little is known empirically or quantitatively 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 the "big push" in catalyzing its economic development (e.g., Murphy et al., 1989). Thus, our setting provides a valuable opportunity to explore the effects of such a policy.

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 industrial technology adoption contracts 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 over the period 1970 to 1982. The dataset was constructed by manually collecting and digitizing adoption-related contract documents that firms were required to report to the government authorities. In our context, technology adoption refers to the transfer of industrial knowledge, defined as the exchange of blueprints or the provision of training services by foreign engineers, aimed at facilitating mass industrial 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, resulting in a fourfold increase in new contracts made by heavy manufacturing firms during the sample period.

Using this constructed dataset, we provide three pieces of empirical 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 and that was driven to an important extent by 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") with firms that received the approval from the government to pursue foreign technology and made a contract with a foreign firm but *failed* to adopt or were *delayed* in adopting technology because the foreign firm canceled the contract because of circumstances seemingly unrelated to the South Korean firms ("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, in which the treatment effects are estimated only based on comparisons between winners and never-treated or not-yet-treated losers. We find that 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 covariates. To identify the spillovers, we propose an IV strategy based on business groups' spatial networks of affiliated firms across region-sectors (Moretti, 2021). We use the 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%, 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 higher local adopter shares led to a higher probability of a firm signing a new technology adoption contract.

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 (Allen and Donaldson, 2022). This lag introduces dynamics to the model, with the share of adopters becoming a time-varying state variable. The model features a 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 from a combination of the spillovers and the fact that fixed adoption costs are in units of final goods. The spillovers from the previous period reduce fixed adoption costs in the current period, inducing more firms to adopt modern technology.

The model rationalizes the possibility of the big push. We demonstrate analytically that dynamic complementarity can lead to multiple steady states: a "pre-industrialized" one with a low adopter share and low aggregate productivity and an "industrialized" one with a high adopter share and high aggregate productivity. 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 an initial condition that would otherwise converge to the pre-industrialized state.

Importantly, we do not impose the existence of multiple steady states a priori. Depending on values of the parameters that govern the direct productivity gains and the spillovers, the model may or may not feature multiple steady states. Consequently, in this model, the success of the big push becomes a quantitative question.

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 firm-level 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 map the model's key parameters that determine the existence of multiple steady states to the reduced-form estimates.

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 GDP share and its export share to total exports would have been 18% and 42% lower, respectively, compared with the steady state of the baseline economy with the policy.

Related literature Our paper contributes to three strands of the literature. First, it relates to the literature on multiple equilibria and the big push (e.g., Rosenstein-Rodan, 1943; Herrendorf et al., 2000; Hirschman, 1958; Murphy et al., 1989; Matsuyama, 1995; Redding, 1996; Rodríguez-Clare, 1996; Ciccone, 2002; Davis and Weinstein, 2002; Redding et al., 2011; Diodato et al., 2022; Alvarez et al., 2023). Our contribution lies in quantitatively exploring the possibility of the big push and evaluating the actual big push policy. Our model combines heterogeneous firm models with discrete technology adoption choices (Melitz, 2003; Yeaple, 2005; Bustos, 2011) and the dynamic spatial model developed by Allen and Donaldson (2022). Using this model, we find the big push can explain South Korea's industrialization and change its comparative advantage.[2] Kline and Moretti (2014) document limited effects of the big push through the Tennessee Valley Authority program in the US due to a constant agglomeration elasticity. Buera et al. (2021) study complementarity in technology adoption and its interaction with distortions. Unlike these two papers, in our model, a combination of local spillovers from adoption and the fact that fixed adoption costs are in units of final goods are the source of multiple steady states.

Second, this paper adds to the empirical literature on firm-level effects of industrial technology

[2]For dynamics of comparative advantage, see, e.g., Levchenko and Zhang (2016), Arkolakis et al. (2019), Schetter (2019), Atkin et al. (2021), Cai et al. (2022), and Pellegrina and Sotelo (2021).

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 industrialization. Our spillover findings align with previous studies on spillover effects of foreign direct investment or new technologies (e.g., Keller, 2002; Javorcik, 2004; Giorcelli, 2019; Bai et al., 2020; Alfaro-Ureña et al., 2022; Bianchi and Giorcelli, 2022). The comprehensive coverage of industrial technology adoption allows us to integrate these findings into a structural model to quantify the aggregate effects of technology adoption.

Third, this paper relates to the literature on South Korea's growth miracle (e.g., Young, 1995; Lee, 1996; Ventura, 1997; Connolly and Yi, 2015; Itskhoki and Moll, 2019). In line with Rodrik (1995), this paper focuses on how South Korea *got its interventions right* by promoting technology adoption. Two closely related papers are Lane (forthcoming) 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 uses novel data on technology adoption and 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-term effects of the policy documented in these two papers. Choi and Shim (2023) use the similar technology adoption data but study relative benefits and costs of technology adoption over innovation depending on stages of development. Related to Liu (2019), who studies sectoral interventions under market imperfections and production networks, we quantitatively find large effects of productivity spillovers of the big push via IO linkages.

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 on the firm-level effects of technology adoption. Section 4 introduces a simple model that provides an analytical characterization of the potential multiple steady states 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. Our dataset covers manufacturing firms and we classify these firms into 10 broad 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 can be found in Appendix Section A.

Technology adoption We manually collected and digitized firm-level data on technology adoption from official documents related to technology contracts, obtained from the National Archives of Korea and from the survey published by the Korea Industrial Technology Association.[3] These documents provide information about the names of domestic and foreign contract parties, as well as the 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. 95% of the contracts involved the transfer of industrial knowledge, defined as the exchange of blueprints or the provision of training services by foreign engineers.[4]

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, exports, 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 70% of manufacturing gross output. To the best of our knowledge, this paper is one of the first to utilize firm panel data from 1970s South Korea.[5]

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 use this subsidy information to serve as control variables and to assess the validity of 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 targeted firms access to foreign credit and provided guarantees for this credit once it was granted.[6] 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

[3]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 received 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 Economic Planning Board met every month and discussed new technology contracts. The National Archives of Korea collected and preserved the documents the Economic Planning Board examined in its monthly meetings.

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

[5]An exception is Choi and Levchenko (2023), who also use the same dataset.

[6]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.

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), IO tables from the Bank of Korea, and regional population data from the Population and Housing Census.

2.2 Late Industrialization in South Korea

In late 1972, the Korean government launched the Heavy and Chemical Industry (HCI) Drive to modernize and promote heavy manufacturing sectors, including chemicals, electronics, machinery, steel, non-ferrous metal, and transport equipment. 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, forthcoming).[7] The heavy manufacturing sectors, which were related to the arms industry, were targeted to modernize South Korea's military forces and achieve 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).[8] Technology adoption was the main means of technology transfer from foreign developed economies to South Korea.[9]

While at the beginning of our analysis period its GDP share of the heavy manufacturing sector was only 6%, South Korea achieved a remarkable takeoff during the sample period, surpassing Mexico by the mid-70s and the US by 1982 (Panel A of Figure 1).[10] Our data reveal that this industrialization

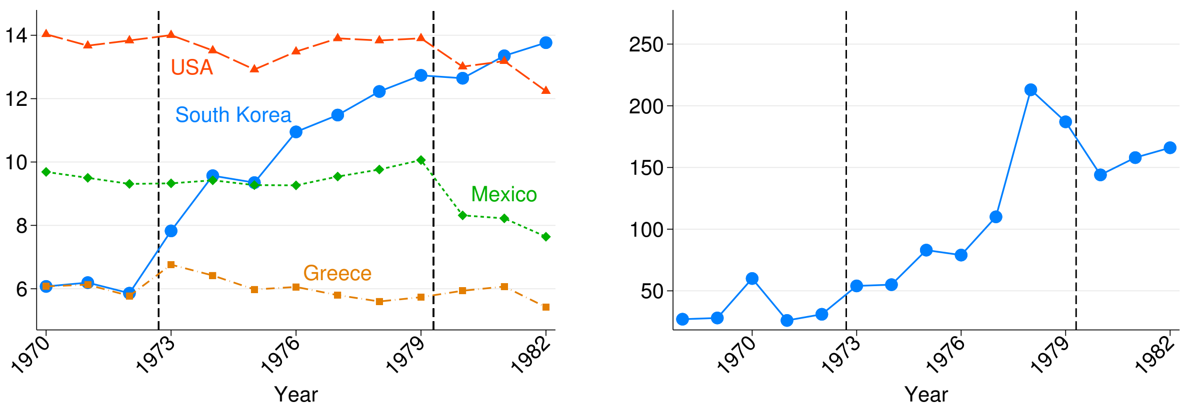
[7]After the Vietnam War, in the Nixon Doctrine (1969), President Nixon demanded more responsibility from the United States' East Asian allies for their self-defense instead of relying on the US military. The doctrine posed a threat to South Korea's national defense because of rising military tension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

[8]"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).

[9]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 because of government regulations on FDI (Kim, 1997, p. 42-43).

[10]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%, respectively, between 1970 and 1982.

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.

pattern 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.

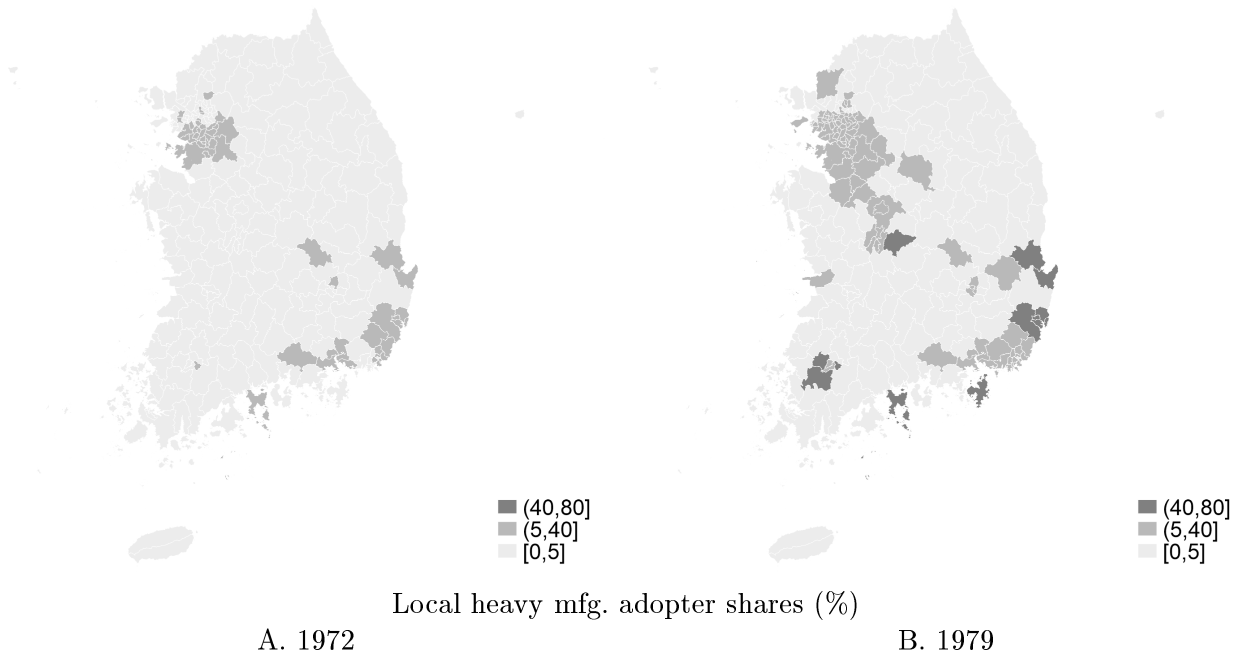
The narrative of the one-time policy and the rapid pattern of industrialization have led to conjectures about the big push behind South Korea's economic development. Later, we show that the local spillovers and complementarity can explain the possibility of the big push. In fact, these local effects 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.[11]

[11] Related to these three findings, we give the 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, p.210-211), and the facilitation of further adoption due to the availability of cheaper domestic capital inputs relate to these three findings (POSCO, 2018, p.138-141). See Appendix Section B.1 for more details.

Figure 2. Geographic Concentration of Technology Adoption Activity



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.

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 were *delayed* in adopting because of 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 control) as firms that made contracts with foreign firms that got approved by the government but failed to adopt or were delayed in adopting foreign technology because the foreign firm canceled the contract for reasons that were external to the South Korean firm. Examples include cancellations due to foreign firms' bankruptcy, changes in their management team, or their sudden requests to change contractual clauses after making a deal. We exclude cancellations by Korean firms, such as their 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 manually collect the cancellation episodes by reading these documents from the archive.

Among these losers, there are two types: delayed-adopters and never-adopters. The delayed-adopters are firms that eventually adopted foreign technology, but the timing of the adoption was delayed due to the cancellations. The never-adopters are firms that never adopted technology after the cancellations. 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 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. On average, these matched winners and losers were 7.4 times larger than the average firm in the entire sample.[12]

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 zero. 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.

To expand the number of observations and extend our analysis over longer periods, we supplement our primary firm balance sheet data with information from KIS-VALUE. It includes firm balance sheet data recorded after 1982 for a subset of our main dataset, which comprises relatively large-sized firms from our main data.[13] However, it still covers the matched winners and losers because

[12]The mean of log sales for these matches was 17.5, whereas the mean for the entire sample was 15.5 (Appendix Tables A1 and B1).

[13]KIS-VALUE covers firms with assets above 3 billion Korean Won, which is equivalent to 2.65 million 2015 US dollars.

these matched firms are larger than the average. We use this supplementary data exclusively for the winners vs. losers research design.

One issue with estimating Equation (3.1) is the staggered rollout design that leverages the 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 the 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 successful adoption, 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, which supports 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 the US Patent and Trademark Office (USPTO), where patenting activities are interpreted as indicators of performance of foreign firms. We find that differences in various measures of patent activities are not statistically significant between the two groups, which rules 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 with 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 the variation comes from the 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.[14] We account for the possibility that adoption may affect the underlying TFP process by adapting the estimation procedure of De Loecker (2013). We lose some samples for TFP^{rr} due to missing employment information.

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. Four years after the adoption, winners' sales and TFP^{rr} experience increases of 117% and 62%, respectively, with persistent effects over time. On average, log sales and TFP^{rr} increased by 92% and 64%, respectively (Appendix Table B4).[15] 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.[16]

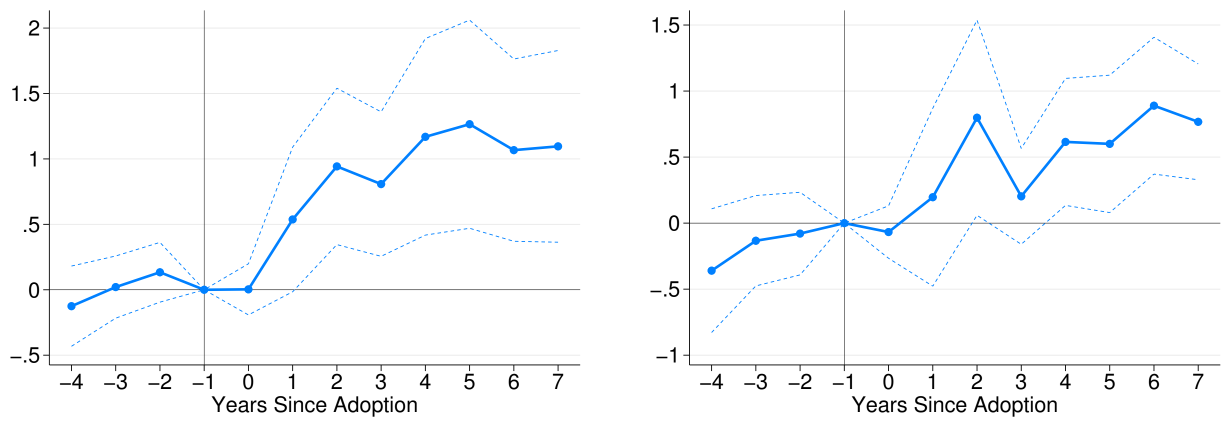
The TWFE estimator also shows that adopters' sales increased after the adoption, but it exhibits increasing pre-trends at $t = -4$, and its magnitude was 75% smaller than that of the baseline. Despite the observed increase in sales, however, the TWFE estimates for TFP^{rr} remain flat after the adoption. 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. After the adoption, the TWFE coefficients become 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

[14] 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. We cannot estimate gross output production function as in Gandhi et al. (2020) due to the lack of data on intermediate inputs.

[15] We calculate these average effects from the estimates of the following regression model: $y_{it} = \beta(\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]) + \delta_{im} + \delta_{mt} + \epsilon_{imt}$, 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 (Appendix Table B4).

[16] They find that technology transfers increased the TFPQ of Chinese steel plants by 25% after six years. Under 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 for sales imply an increase in TFPQ of 35% to 57%.

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



A. Log sales

B. $\mathrm{TFP}^{\mathrm{rr}}$

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 $\mathrm{TFP}^{\mathrm{rr}}$ 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 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.

Robustness We rule out alternative explanations against our findings. One possibility is that foreign firms sold technology tailored to their inputs, leading to increases in sales or $\mathrm{TFP}^{\mathrm{rr}}$ 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 explanation unlikely (Appendix Figure B2). We also exclude the possibility of demand shocks induced by government military spending, as none of the matched winners and losers were firms that had military contracts with the government.[17] Finally, the raw plot of the 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

[17] Since the implementation of the Act on Special Measures for Defense Industry in 1973, all government military contracts have been awarded to pre-registered firms. From the list of these firms, we can identify whether the winners and losers were among the pre-registered firms.

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)
# Cl. (Firm or Region)	91	80	91	77	55	77
N	644	484	644	24131	12657	24131
Match×Firm FE	✓	✓	✓			
Match×Year FE	✓	✓	✓			
Firm FE				✓	✓	✓
Region×Sector×Year FE				✓	✓	✓

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.

Figure B1).[18]

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 estimation samples without missing employment, alternative numbers of winners matched with each loser, and two-way clustering at the match and firm levels.

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

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

$N_{(-i)nj,t-h}$ is the total number of firms in region-sector nj in year $t-h$ excluding firm i. $N^T_{(-i)nj,t-h}$ is the number of firms in nj that ever made a contract with any foreign firms in $t-h$ excluding i. 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 the 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$^{\text{rr}}$. 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 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 because of the well-documented fact that larger firms grow slower. Some specifications include additional observables $\mathbf{X}_{injt}$. We two-way cluster standard errors at the region and business group levels. 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 not only spillovers but also

[18] While increased local competition could potentially have negative effects on the losers, it is important to note that the manufacturing sectors are highly tradable. Moreover, our spatial unit of analysis is quite granular, as we are examining firms within 135 sub-divided regions in a country of similar size to Indiana in the US. Therefore, it is unlikely that this competition will have a significant impact.

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 are time spans that 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, restricting to the never-adopter sample can cause a selection problem. However, the direction of the OLS bias 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 could lead to a downward bias. Also, as our data do not cover the universe of firms, measurement error in local shares could 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.[19]

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

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

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 t_0. $\tilde{N}^{\text{p}}_{(-i)nj,t-h}$ is the predicted number of firms in region-sector nj in year $t-h$, excluding i: $\tilde{N}^{\text{p}}_{(-i)nj,t-h} \equiv g_{(-n)j} \times N_{(-i)nj,t_0-h}$, where $g_{(-n)j}$ is the national-level growth of the number of sector j firms, excluding those in region n, and $N_{(-i)nj,t_0-h}$ is the number of firms in region-sector nj, excluding firm i, in year t_0-h. We construct the IV as the long-difference of $Z^{\geq 25\text{km}}_{inj,t-h}$:

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

We exclude firms located within 25km due to potential spatial interactions with neighboring firms

[19] Giroud et al. (2023) also study the role of the plant-level networks of multi-region firms in the propagation of local productivity spillovers through their shared knowledge.

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 OLS estimate. Column 2 reports the IV estimate, which is around 4. The estimate implies that a 1 percentage point increase in adopter shares leads to 4% higher sales. The IV estimate is both larger and more precise than the OLS estimate because the IV corrects for the measurement errors and the endogeneity issues. The IV is strong, with a first-stage coefficient of 0.1 and a Kleibergen-Paap F-statistics (KP-F) of 29.4 (Appendix Table B5). In Panel B, the dependent variable is TFP^{rr} growth. Although the statistical significance weakens as the sample size decreases due to missing employment data, we find that a 1 percentage point increase in adopter shares leads to 1% higher TFP^{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 a 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):

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

where $\mathcal{F}_{mkt}$ is the set of firms in region-sector mk operating in year t. We proxy internal trade costs using the distance between regions Dist_{nm}, and set χ equal to 1.1 (Costinot and Rodríguez-Clare,

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								
$\triangle\text{Share}_{(-i)nj,t-2}$	0.37	3.93***	3.87***	4.16***	3.71***	3.82***	4.04***	3.84***
	(0.42)	(0.93)	(0.93)	(1.03)	(0.89)	(0.90)	(0.89)	(0.94)
KP-F		30.12	29.03	38.26	29.04	26.35	38.57	41.96
# 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								
$\triangle\text{Share}_{(-i)nj,t-2}$	−0.48*	0.95*	0.87	1.03*	0.95*	0.91*	0.85	0.76
	(0.27)	(0.52)	(0.55)	(0.54)	(0.53)	(0.53)	(0.54)	(0.63)
KP-F		29.37	29.52	33.94	25.90	27.69	40.79	45.13
# 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 region and business group levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

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 of 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 region-sector nj in year t, excluding firm 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 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 a port dummy interacted with the changes in import tariffs. Because import tariffs can affect firm performance through the costs of imported intermediates, we also control for the port dummies interacted with the changes in 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 jointly control for all of these additional controls.

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 local 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 past sales growth (Appendix Table B6).

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 indicating 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, which supports our functional form (Appendix Table B8). In particular, in our setting, the spillover elasticity is nonlinear in logs in contrast to Kline and Moretti (2014) who find a log-linear elasticity. This discrepancy may arise from different sources of spillovers.

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 the fact that never-adopters' productivity improved due to local spillovers. We also check the sensitivity to omitting y_{it_0} and using an alternative lag of 3.

We examine how firm entry and exit are affected by adopter shares, detailed in Appendix Section B.2. The estimates for firm entry and exit are not precise, indicating that our baseline findings are not unduly influenced by firm entry and exit.

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 sample that excludes firms in regions where heavy manufacturing industrial complexes are constructed, a single difference between 1973 and 1980; with non-missing employment; and 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 1973 and 1980:

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

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 the ever-adoption status that is used to construct the adopter shares in Equation (3.4). For example, if a firm had not adopted any foreign technologies previously but made the first contract in year t, both $\mathbb{1}[\text{New Contract}_{it}]$ and the ever-adoption status 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 the ever-adoption status

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	0.63^{***}	0.62^{***}	0.65^{***}	0.66^{***}	0.62^{***}	0.62^{***}	0.65^{**}
	(0.10)	(0.22)	(0.22)	(0.24)	(0.23)	(0.22)	(0.22)	(0.25)
KP-F		11.47	10.84	12.62	11.19	10.79	14.05	14.09
# 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 region and business group levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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.

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 set of fixed effects used in the spillover regression. The identifying assumption remains the same as that of the IV of the spillover regression. The positive β suggests that more local firms adopting technology increased the likelihood of firms adopting new foreign technology. Standard errors are two-way clustered at the region and business group levels.

Columns 1 and 2 of Table 3 report the OLS and IV estimates, respectively. Once endogeneity is corrected for, 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). The IV is strong with a *KP*-F of 11.5 (Appendix Table B5). 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 B6). Additionally, we perform a set of robustness checks similar to those of the spillover regression (Appendix Table B10).

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 finding indicates the potential presence of positive externalities associated with technology adoption. Furthermore, the observed complementarity in adoption decisions suggests the potential existence of a feedback loop, wherein 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 feedback loop, firms would have continued to adopt foreign technologies even after subsidies were 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 Steady States

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 lead to multiple steady states. When multiple steady states exist, a big push that temporarily provides subsidies for technology adoption can have a permanent 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 1. Each firm produces a unique variety. 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 a demand curve $q_{it} = p_{it}^{-\sigma} P_t^{\sigma} Q_t$ where q_{it} is the quantity demanded, p_{it} is the price charged by them, $Q_t = (\int q_{it}^{\frac{\sigma-1}{\sigma}} \mathrm{d}i)^{\frac{\sigma}{\sigma-1}}$ is the aggregate quantity, and $P_t = (\int p_{it}^{1-\sigma} \mathrm{d}i)^{\frac{1}{1-\sigma}}$ is the ideal price index. $\sigma > 1$ is the elasticity of substitution across varieties. Firms optimally charge constant markups $\mu = \sigma/(\sigma-1)$ over their unit costs $p_{it} = \mu w_t / z_{it}$, 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:

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

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 $f(\lambda^T_{t-1})$, common across firms, is the adoption spillover that increases with the adopter share in the previous period λ^T_{t-1}. In Appendix Section C.4, we provide two sets of microfoundations that generate the spillovers through labor mobility and knowledge transfers.[20] The third term ϕ_{it} is exogenous productivity, which is 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:

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

where δ is a parameter that governs the strength of the spillover. Following Allen and Donaldson (2022), we allow the spillovers to operate with a one-period lag rather than operate contemporaneously. The chosen functional form and the inclusion of a lag in the spillover effect align with the specification of the spillover regression.[21] We view that allowing for a lag is more realistic because it may take some time for knowledge to be locally diffused. Also, as discussed by Adserà and Ray (1998), allowing for a lag permits 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:

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

where π_{it} is i's final profits. 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 period t. Due to this externality, the social returns to adoption exceed the private returns, leading to suboptimal adoption rates below the socially optimal level. With

[20] 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 are reduced with higher adopter shares due to knowledge transfers.

[21] This functional form is further supported by the robustness checks in Appendix Table B8.

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

$$(\bar{\phi}_t^T)^{\sigma-1} = \frac{\sigma P_t F^T}{(\eta^{\sigma-1}-1)(\mu w_t)^{1-\sigma} f(\lambda_{t-1}^T)^{\sigma-1} P_t^{\sigma} Q_t}. \tag{4.1}$$

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

Equilibrium In each period, given λ_{t-1}^T, 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-1}^T, λ_t^T is determined in t; and then given λ_t^T, λ_{t+1}^T is determined in $t+1$, and so on.

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

Under the Pareto distribution (Assumption 1(ii)), 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 $\lambda_t^T = \lambda_t^T(\lambda_{t-1}^T;\eta,\delta)$ in each period conditional on λ_{t-1}^T:

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

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

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

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

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 steady states Assumption (i) ensures the unique static equilibrium for each period.[22] Given any initial adopter share λ_{t_0}, because the static equilibrium is

[22] 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, may arise. Higher shares increase competition but also decrease fixed adoption costs by lowering P_t, which incentivizes more and less adoption, respectively. $A(\lambda_t^T)^{2-\sigma} = A(\lambda_t^T)^{1-\sigma}A(\lambda_t^T)$ 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 weaker and more firms adopt technology with higher shares, which generates static complementarity and potential multiple static equilibria, the setup studied by Matsuyama (1995) and

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, the likelihood of other firms adopting technology increases in the current period, consistent with the third empirical finding. The fixed adoption costs in units of final goods and the spillovers are the sources of this complementarity. The spillovers from the previous period's adoption share raise all firms' productivity. This higher productivity lowers the P_t and reduces total expenditures on fixed adoption costs $P_t F^T$, further incentivizing more firms to adopt technology.[23] Moreover, the equilibrium adoption share λ_t^T increases with values of η and δ. Higher values of η magnify the direct gains, while higher values of δ strengthen the dynamic complementarity.

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

Proposition 1. *Under Assumption 1,*

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

(ii) (Dynamic complementarity) $\partial\lambda_t^T(\lambda_{t-1}^T;\eta,\delta)/\partial\lambda_{t-1}^T \geq 0$*;*

(iii) (Comparative statistics) $\partial\lambda_t^T(\lambda_{t-1}^T;\eta,\delta)/\partial\eta \geq 0$ *and* $\partial\lambda_t^T(\lambda_{t-1}^T;\eta,\delta)/\partial\delta \geq 0$*;*

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

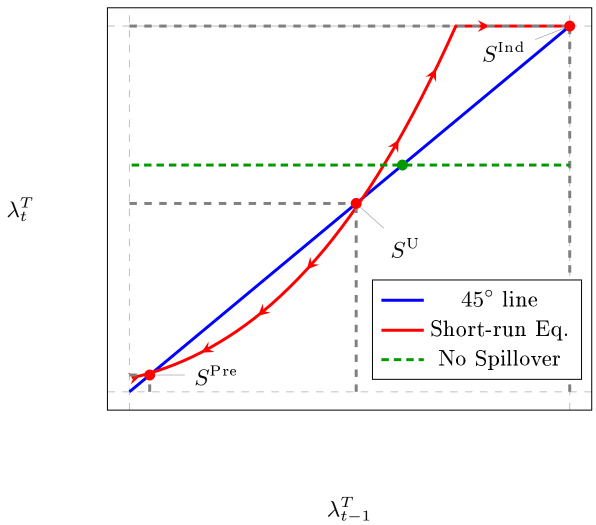
and (v) (Welfare) If multiple steady states exist, these steady states can be Pareto-ranked based on the equilibrium share of adopters.

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.[24] The red locus is defined by Equation (4.3). Each point on the locus represents a short-run equilibrium λ_t^T conditional on the previous equilibrium share λ_{t-1}^T, and the equilibrium moves along the red locus as time passes. The steady state is determined at the point where $\lambda_{t-1}^T = \lambda_t^T, \forall t$ 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,

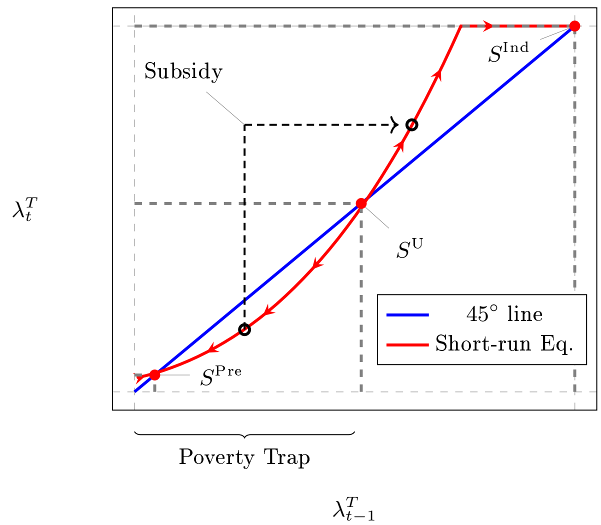
Buera et al. (2021). By imposing $\sigma > 2$, we make the competition effects sufficiently strong to rule out this possibility. Unlike these papers, because we impose $\sigma > 2$, multiple steady states arise only due to the spillovers. Also, commonly calibrated parameter values for σ are larger than 2.

[23] This channel is also consistent with the example of POSCO in Appendix Section B.1.

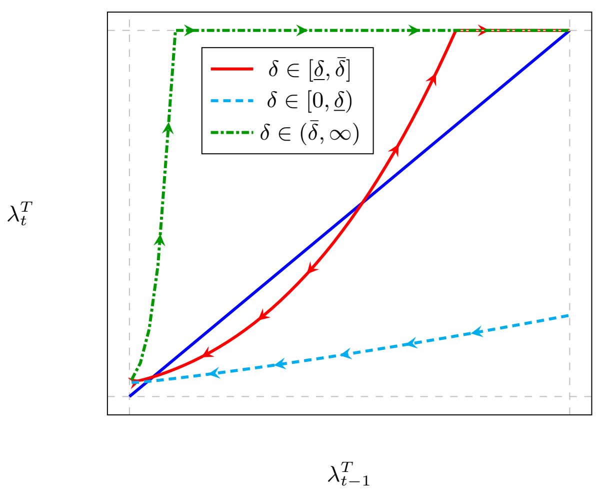
[24] There can be at most three multiple steady states due to the strict convexity imposed by the assumed spillover functional form. The functional form ensures that λ_t^T is strictly convex in λ_{t-1}^T, allowing the red locus in Figure 4 to intersect the 45-degree line at most twice. Alternative functional forms that generate higher levels of nonlinearity can result in more than three multiple steady states.



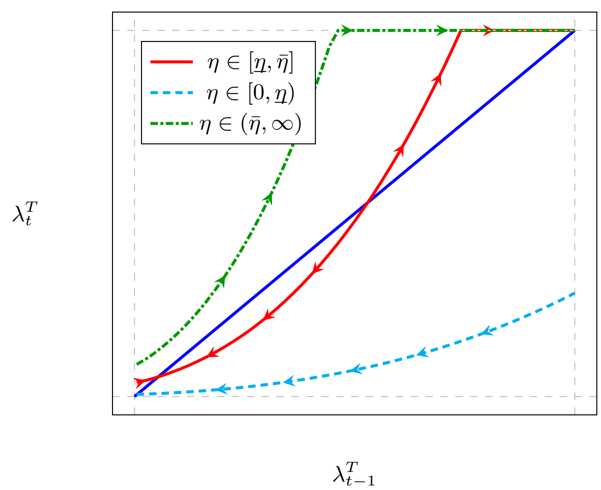
Panel A. Multiple Steady States and Nonlinearity



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.

unstable, and industrialized steady states, respectively. S^{U} is unstable in the 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.

An initial adoption share determines which steady state is realized in the long-run. If the initial condition is given by $\lambda_{t_0}^T \in [0, S^{\mathrm{U}})$ and $\lambda_{t_0}^T \in (S^{\mathrm{U}}, 1]$, the economy converges to S^{Pre} and S^{Ind}, respectively. These steady states can be Pareto-ranked depending on their adopter shares. At S^{Ind}, all firms adopt technology, while S^{Pre} has a smaller adopter share compared with 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. The spillover ($\delta > 0$) generates such nonlinearity. Without the spillover ($\delta = 0$), 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 and the 45-degree lines.

The potential existence of multiple steady states depends on the strict convexity of $f(\lambda_{t-1}^T)$, which ensures that the equilibrium λ_t^T is strictly convex in λ_{t-1}^T. However, our results can be generalized to any functional forms that exhibit strict convexity. Also, note that with the current exponential functional form, there can be at most three multiple steady states because the red locus intersects 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.

Poverty trap and big push The range $[0, S^{\mathrm{U}})$ is commonly referred to as a poverty trap in the literature (Azariadis and Stachurski, 2005; Banerjee and Duflo, 2005). If an initial condition is trapped in the poverty trap, a big push policy that provides a one-time subsidy for adopters' input costs or fixed adoption costs can have permanent effects by moving the economy out of the trap (Panel B). This is summarized in Proposition 2. Note that, in this model, only multiple steady states can rationalize the permanent effects of a one-time policy. With a unique steady state, a one-time subsidy would temporarily shift the short-run equilibrium curve, but the economy would ultimately converge back to its original steady state once the subsidy ends.

Proposition 2. *(Big push) Suppose the multiple steady states exist and the economy is initially in the poverty trap, $\lambda_{t_0}^T \in [0, S^U)$. 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 the 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 $\eta \in [\underline{\eta}, \bar{\eta}]$, where 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 modern technology, regardless of the previous shares, and vice versa. This leads to a single intersection point. These comparative statistics provide a potential explanation for why South Korea underwent the remarkable transformation 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 the values fell within a range that generated multiple steady states.[25]

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 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. We normalize total population to 1.

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 intermediate inputs. They aggregate all available varieties from all regions and countries using a CES aggregator with the price index given by

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

p_{injt} is a price charged by firms, and Ω_{mj} is the set of available sector j varieties in region m. Because there are no fixed export costs for internal trade, each region has the same set of available varieties. P^f_{jt} is an exogenous import cost and t_{jt} is an import tariff.

Home firms take foreign demand D^x_{jt} as exogenously given and face the demand schedule of $p_{it}^{-\sigma} D^x_{jt}$. D^x_{jt} also captures any common barriers to 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.

[25] η can be related to the absorptive capacity of new technology, and δ to the degree of barriers to 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 with 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.

Production Firms have a constant return to scale (CRS) Cobb-Douglas production function:

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

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

The productivity term z_{it} consists of three components as in the simple model, but the spillovers $f(\lambda_{nj,t-1})$ increase in the previous region-sector adopter shares $\lambda_{nj,t-1}$, 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.[26] 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. The unbounded Pareto of the simple model is the limiting case of the bounded Pareto that can be achieved by letting $\kappa \to \infty$. $\phi_{njt}^{\min}$ 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 $0 \leq s_{njt} \leq 1$, varying across regions, sectors, and periods.[27] With the subsidies, adopters' input costs become

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

The government imposes a common labor tax τ_t^w to finance the subsidies.[28] The government budget is balanced every period.

We assume that goods required for the fixed adoption costs are produced using the following Cobb-Douglas technology:

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

F_{nj}^T is a parameter that governs the overall cost level, which potentially varies across region-sectors.

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

[27] This is because the government provided subsidies to adopters for the purchases of capital equipment related to adopted technologies, and in our model, we interpret new capital equipment as intermediate inputs.

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

γ_j^L and γ_j^k are the Cobb-Douglas shares of the production function. We assign Cobb-Douglas shares identical to those of the production function because of the lack of detailed information regarding intermediate goods used for these fixed adoption costs. Because parts of the fixed adoption costs are in units of final goods, the dynamic complementarity arises. 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 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 the consumption baskets and P_{nt} is their ideal price index. $(1-\tau_t^w+\bar{\pi}_t)w_{nt}$ is the total income, which is the sum of after-tax wages and dividend income.

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 choose 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: $\mathcal{U}_{nmt}^h(\epsilon_{nmt}^h) = V_{mt}\omega_{mt}d_{nm}\epsilon_{nmt}^h$, where ω_{mt} is real wage: $\omega_{mt} = \frac{(1-\tau_t^x+\bar{\pi}_t^h)w_{mt}}{P_{mt}}$. 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 independently and identically 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

$$\mu_{nmt} = \frac{(V_{mt}\omega_{mt}d_{nm})^\nu}{\sum_{m'}(V_{m't}\omega_{m't}d_{nm'})^\nu}.$$

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

Welfare We define the regional welfare of households living in region n in period t as the expected static utility before the realization of the preference shocks (Allen and Donaldson, 2022): $U_{nt} = [\sum_m(V_{mt}\omega_{mt}d_{nm})^\nu]^{\frac{1}{\nu}}$. 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 $\{\lambda_{njt_0}^T, L_{nt_0}\}$ and a path of the fundamentals $\{\phi_{njt}^{\min}, V_{nt}, P_{jt}^f, D_{jt}^x\}$, tariffs $\{t_{jt}\}$, and subsidies $\{s_{njt}\}$, firms maximize profits; households maximize utility; labor and goods markets clear; trade is balanced; 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 nontradable 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.[29] Given these initial values, we solve the model for $t = 1$, which corresponds to 1972 in the data. After solving for $t = 1$, 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 1980 levels. We sequentially solve the model period by period for a 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, $\mathbf{\Theta}^{\mathrm{E}} = \{\eta, \delta, M_{nj}, \theta, \sigma, \gamma^L_j, \gamma^k_j, \nu, d_{nm}, \tau_{nmj}, \tau^x_{nj}, \alpha_j\}$ and $\mathbf{\Theta}^{\mathrm{M}} = \{\kappa, F^x_j, F^T_{nj}\}$. We externally calibrate $\mathbf{\Theta}^{\mathrm{E}}$ and t_{jt}, and internally calibrate s_{njt}, $\mathbf{\Psi}_t$, and $\mathbf{\Theta}^{\mathrm{M}}$ by indirect inference. 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 the log of adopters' sales, we derive the following relationship that can be mapped to the winners vs. losers specification:

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

Match-year fixed effects δ_{mt} capture variables common at the match levels, including local spillovers, unit costs of production, and the market size common across firms within region-sectors.[30] Also, based on the lack of evidence that winners received more subsidies relative to losers, we map the estimates to the pure effects of technology adoption rather than joint effects including subsidies, and assume that subsidies are absorbed out by δ_{mt}.[31] 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 Appendix Table B4).

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

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

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

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	1.30	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 gross output
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.

Taking the log of non-adopters' sales, we obtain the following relationship that can be mapped to the spillover regression:

$$\ln \text{Sales}_{it} = (\sigma - 1)\delta\lambda_{njt}^T + \mathbf{X}'_{njt}\gamma + (\sigma - 1)\ln\phi_{it},$$

where $\mathbf{X}_{njt}$ is 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 from columns 2-8 in Panel A of Table 2.

An alternative mapping based on $\text{TFP}_{it}^{\text{rr}} \propto \frac{\sigma-1}{\sigma}\ln z_{it}$ gives a similar value for δ but a larger value for η ($\eta = 2.2$ and $\delta = 1.2$) (Blackwood et al., 2021).[32] Thus, the baseline calibrated values can be

[32] 2.2 and 1.2 are calculated as $\eta = \exp(\frac{\sigma}{\sigma-1} \times 0.6)$ and $\delta = \frac{\sigma}{\sigma-1} \times 0.9$, where 0.6 is the average effect of the coefficients

considered as lower bounds among the possible mappings.

Migration We parametrize the migration costs as $d_{nm} = (\text{Dist}_{nm})^{\zeta}$, where Dist_{nm} is the distance between regions n and m. We set ν equal to 2 (Peters, 2021).[33] 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 one 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 $\mu_{nm} = exp(\nu\zeta\text{Dist}_{nm} + \delta_n + \delta_m)\epsilon_{nmt}$, where standard errors are two-way clustered at the origin and destination levels. The gravity estimate is $\nu\zeta = 1.39$ and statistically significant at the 1% level.

Iceberg costs and tariffs We parametrize internal iceberg costs as $\tau_{nmj} = (\text{Dist}_{nm})^{\xi_j}$ where ξ_j is the 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. We 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 seven largest ports in South Korea. Any common components of the iceberg costs are not separately identifiable from D^x_{jt}, so we set $\tau^x_{nj} = 1$ for regions with ports. We take import tariffs directly from the data.

The remaining parameters We set the Pareto shape parameter θ equal 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-sector and set $\sum_{n,j} M_{nj} = 1$ (Chaney, 2008). The Cobb-Douglas shares of preference and production functions, 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 $t = 2, 3$, which correspond to 1976 and 1980, and to firms in regions with at least one firm that ever received foreign credit in the data $\mathcal{N}^{\text{s}}$. 35 regions were included in $\mathcal{N}^{\text{s}}$. We assume the same subsidy level $\bar{s}$ across these regions and periods:

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

Adoption cost We parametrize the 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 would become

from the winners vs. losers research design (column 2 of Appendix Table B4) and 0.9 is the average of the IV estimates of columns 2-8 in Panel B of Table 2.

[33]The value of 2 is also in line with the migration elasticity of 0.7 at the annual frequency estimated by Choi (2022) who uses the South Korean migration flow data.

more costly.[34]

Constrained minimum distance We calibrate $\mathbf{\Theta}^{\mathrm{M}}$, $\bar{s}$, 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 $g(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t) \equiv \bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)$ be the distance between a vector of the model moments $\bar{\mathbf{m}}$ and the data counterparts $\mathbf{m}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)$ and let $c(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t) \equiv \mathbf{C}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{C}_t$ be the imposed constraints, where $\mathbf{C}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)$ and $\mathbf{C}_t$ are vectors of the model moments and data counterparts. We calibrate $\mathbf{\Theta}^{\mathrm{M}}$, $\mathbf{\Psi}_t$, and $\bar{s}$ by solving the following constrained minimization problem:

$$\{\hat{\mathbf{\Theta}}^{\mathrm{M}}, \hat{\bar{s}}\} \equiv \underset{\{\mathbf{\Theta}^{\mathrm{M}}, \bar{s}\}}{\arg\min} \left\{ g(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)' g(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t) \right\} \qquad \text{s.t.} \qquad c(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t) = 0. \tag{5.1}$$

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} by 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 nearest distance to the port: $\lambda^T_{njt} = \exp(\beta^T_0 + \beta^T_1 \ln \mathrm{Dist}^{\mathrm{port}}_n) \times \epsilon_{njt}$. The estimated value of β^T_1 is $\hat{\beta}^T_1 = -0.35$, which is statistically significant at the 5% level, 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 magnitude of the benefits from the adoption (direct and spillover effects) and the values of F^T_{nj}, the increases in the adopter shares in 1976 and 1980 relative to those in 1972 are informative about the subsidies because $\bar{s}$ only enters in 1976 and 1980.

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 (5.1) identify $\mathbf{\Psi}_t$ based on the model-inversion logic (Allen and Arkolakis, 2014). We impose the constraints such that sectoral export intensities and import shares, regional distribution of sectoral gross output, and regional population distribution of the model are exactly fitted to the data counterparts in 1972, 1976, and 1980. The

[34] 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.

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.

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.[35] D^{x}_{jt} and P^{f}_{jt} are identified by the sectoral export intensities and import shares, $\phi^{\min}_{njt}$ by the regional sectoral gross output distribution, and V_{nt} by the population distribution.

Estimation results We internally calibrate 6 parameters to match 9 target moments. 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 heavy manufacturing sector's fixed adoption cost is about 71 times larger than its fixed export cost–calculated as the median of $c_{njt}F^{T}_{nj}/w_{nt}F^{x}_{j}$ across regions and periods.

Although we do not directly target the employment share, the calibrated model approximates the evolution of the employment shares between 1972 and 1980 quite well, which is the non-targeted moment (Figure 6). However, because we do not directly target data moments after 1980, our model does not explain well the evolution of these outcomes after 1980.

[35] 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 normalize V_{nt} of the reference region to 1 for each period.

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 with the policy to those of the counterfactual economy without the policy. Figure 5 reports this comparison. The pattern of industrialization and its comparative advantage would have evolved differently because the counterfactual economy converges to an alternative less-industrialized steady state.[36] We compare the heavy manufacturing sector's share of value added with GDP, the share of employment with total employment, and the share of exports with total exports. In this alternative steady state, the GDP share would have decreased by 18% (3.1 percentage points), the export share by 42% (27.1 percentage points), and the employment share by 15% (1.7 percentage points). The aggregate welfare gains of the baseline are 8.2% permanently higher than the counterfactual once the economies reach the 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.[37]

Figure 6 illustrates each region's average heavy manufacturing productivity and real income in the steady states. In Panel A, the x- and y-axes are each region's steady state heavy manufacturing productivity, $M_{nj}[\int z_{it}(\phi)^{\sigma-1} dG_{njt}(\phi)]^{1/(\sigma-1)}$, in the baseline and counterfactual. Each dot represents each region and dots located below the 45-degree line represent regions that had higher productivity in the baseline than in the counterfactual. Only three regions gained higher productivity. This fact implies that the aggregate industrialization patterns documented in Figure 5 were driven by the local productivity improvement of these three regions rather than the uniform improvement across the whole country. 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, in all but one region, real income was higher in the baseline because the large productivity gains of the three regions were shared with other regions through trade and migration linkages.

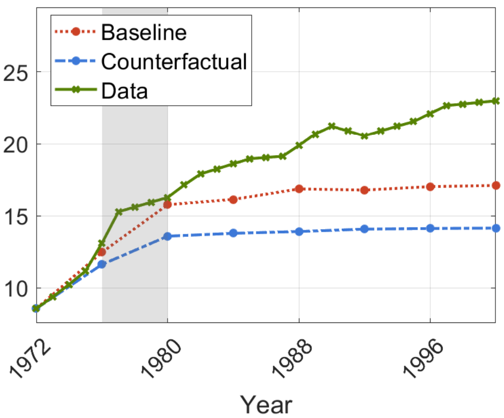
These results contrast with those of Kline and Moretti (2014) who find that, with a constant agglomeration elasticity, spatial reallocation of economic activities does not have aggregate effects as gains from some regions cancel out costs of others. Our setup deviates from theirs in several ways. First, the source of multiple steady states differs. In our setup, not only the spillovers but also the fact that fixed adoption costs are in units of final goods play a critical role as in Buera et al. (2021), and the strict convexity of $f(\lambda_{t-1}^T)$ is the key in generating multiple steady states.[38] Second, we

[36] 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 spatial interactions through trade and migration (Allen and Donaldson, 2022).

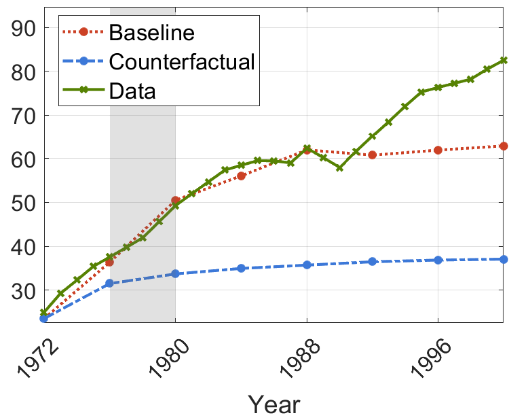
[37] The calibrated subsidies are not optimally designed, so there is room for welfare improvement. Analyzing the optimal subsidy in this economy is outside the purview of this paper. For the optimal policy, for example, see Bartelme et al. (2020), Fajgelbaum and Gaubert (2020), and Lashkaripour and Lugovskyy (2020) in the static setting.

[38] Even with a constant agglomeration elasticity, as long as it is larger than 1, our setup can still feature multiple steady states, contrasting it with their setup.

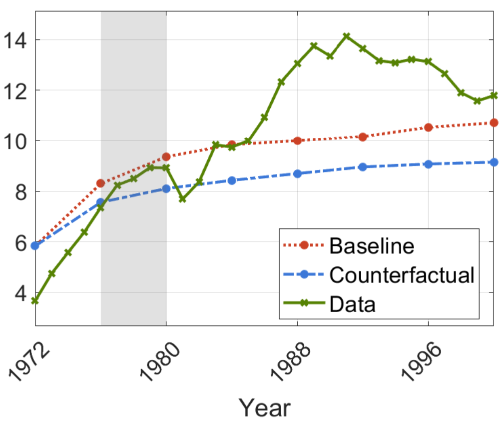
Figure 5. Aggregate Effects of the Big Push



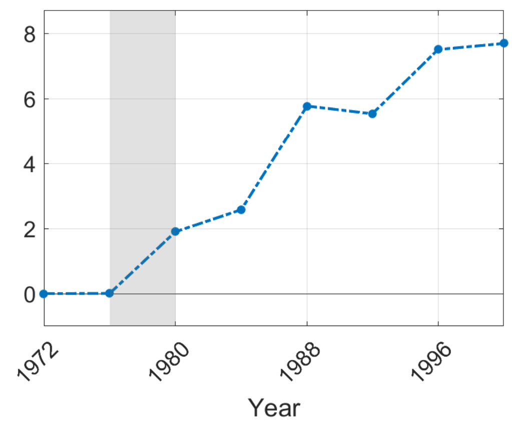
A. Heavy mfg. GDP share (%)



B. Heavy mfg. export share (%)



C. Heavy mfg. emp. share (%)



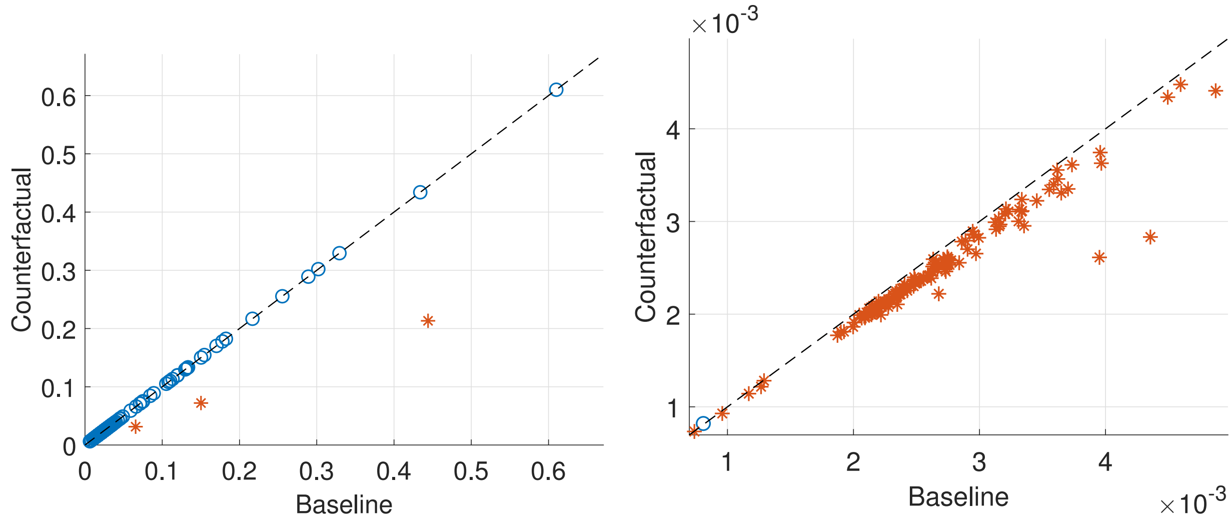
D. Aggregate welfare gain (%)

Notes. This figure plots the baseline and counterfactual results. The gray-colored area denotes the policy period in which subsidies are provided. 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.

impose a spillover elasticity nonlinear in logs (or a linear semi-elasticity) as evidenced by the data. This discrepancy may arise from different types of spillovers in the two papers: technology adoption vs. density of manufacturing employment. Lastly, region-sectors are linked through IO and trade linkages.

International trade Because of the Cobb-Douglas production and utility, consumers and firms spend a constant fraction of their total expenditures. Therefore, in the closed economy, which is

Figure 6. Local Productivity and Real Income



A. Steady state local productivity

B. Steady state local 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 limiting case of the open economy ($P^f_{jt} \to \infty$, $D^x_{jt} \to 0$), even if the big push induces the economy to reach an alternative steady state, the GDP shares would be constant across steady states despite different adoption levels. However, in the open economy, higher productivity in the heavy manufacturing sector increases its exports in the industrialized steady state, which leads to higher GDP shares when compared with the less-industrialized steady state. Thus, the industrialization relates to changes in comparative advantage induced by technology adoption.[39]

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.[40] First, international trade makes firm 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 are another source of the scale complementarity

[39]Previous papers in the trade literature have documented the evolution of comparative advantage (e.g., 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.

[40]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 do not exist. See Appendix Section C.3.

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^x_{jt}	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			
$\eta = 1.1$	2.1	19.9	1.6
$\delta = 0.7$	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 the magnitude of IO linkages is reduced by 10% in 1976 and 1980. Panel C reports the results with different parameter values.

(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.

To examine quantitative aspects of the 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% ($\tilde{\gamma}^L_j = 1 - \sum_k \tilde{\gamma}^k_j$, $\tilde{\gamma}^k_j = 0.9 \times \gamma^k_j$, $\forall j, k \in \mathcal{J}$). In all exercises, in order to emphasize the interaction between scale and dynamic complementarities, we make 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) and Lane (forthcoming). Migration plays 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 depend 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 the estimates for the direct effects and the spillovers, which correspond to $\eta = 1.1$ and $\delta = 0.7$, and repeat the counterfactual analysis using these alternative values. Note that $\eta = 1.1$ is also consistent with the TWFE estimate (column 4 of Table 1). 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 toward different steady states, 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 $\{L_{nt}, M^T_{njt}\}$ backward-looking. This simplification allows us to preserve the rich spatial heterogeneity and connect the model to the empirical findings while facilitating computational implementation.[41] 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.

7 Conclusion

We empirically and quantitatively examine the effects of technology adoption on South Korea's late industrialization. We find that technology adoption brought not only 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 toward a more industrialized steady state.

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

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

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ONLINE 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 the calendar 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 production locations to the 2010 administrative divisions of South Korea. We classify firms into 10 sectors, four of which are classified as heavy manufacturing, as reported in Table A2. The numbers inside the parenthesis are ISIC Revision 3.1 codes. Table A1 reports the summary statistics.

Table A1: Summary Statistics

	Mean (1)	Med. (2)	SD (3)	Obs. (4)
Log sale	15.46	15.34	1.76	29,786
Log emp.	5.22	5.12	1.34	19.909
Log fixed assets	14.08	13.96	2.03	24,648
Log assets	15.25	15.06	1.82	29.755
$\mathbb{1}$[New Contract]	0.03	0	0.17	29,786

Notes. This table reports the summary statistics. $\mathbb{1}$[New Contract] is a dummy indicating whether a firm make a new adoption contract in a given year.

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

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

Table A2: 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.

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.

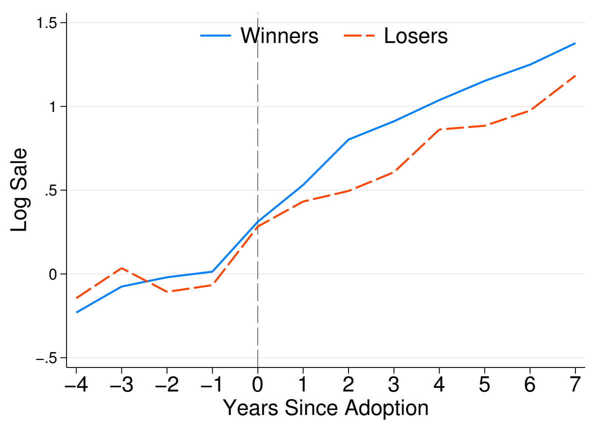
Due to the local labor mobility of engineers across firms, the benefits of POSCO's newly acquired technology were not limited to its own operations. The engineers who received training from the Japanese engineers at POSCO gained new knowledge through learning by doing and reverse engineering. Subsequently, these engineers moved to smaller local mills or capital goods producers, diffusing their knowledge and enhancing 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 been imported in the early 1970s (Enos and Park, 1988, p. 210-211). This knowledge diffusion through labor mobility aligns with our second finding on local spillovers.

Furthermore, the diffusion of knowledge 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, p.138-141). For the new expansion of production facilities in 1980, the share of expenditures on locally-produced capital equipment was 35%, compared to 12% when they first adopted technology in 1968. This demonstrates the role of local firms in reducing the costs of adoption, consistent with our third finding and the model specification of fixed adoption costs in Section 4.

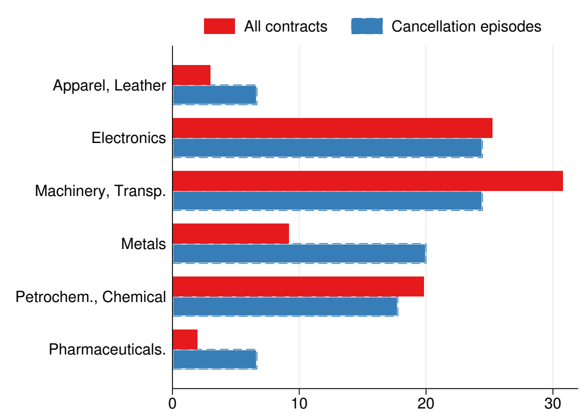
B.2 Additional Figures and Tables

Firm entry and exit We consider dummies indicating whether a firm exits or enters in 1979 or 1980 as dependent variables. We estimate Equation (3.4) using the sample of firms operating in 1972 or 1973 for the exit dummy and using the sample of firms operating in 1979 or 1980 for the entry dummy. Table B7 reports the results. We consider the never-adopter sample and the full sample that includes both ever- and never-adopters. The estimates for firm entry and exit are not precise, with the exception for firm entry based on the never-adopter sample, where we find a marginally significant positive estimate at the 10% level. These results provide support for the robustness of our baseline findings, indicating that they are not unduly influenced by firm entry and exit.

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



A. Trends around the event



B. Shares of contracts by sector (%)

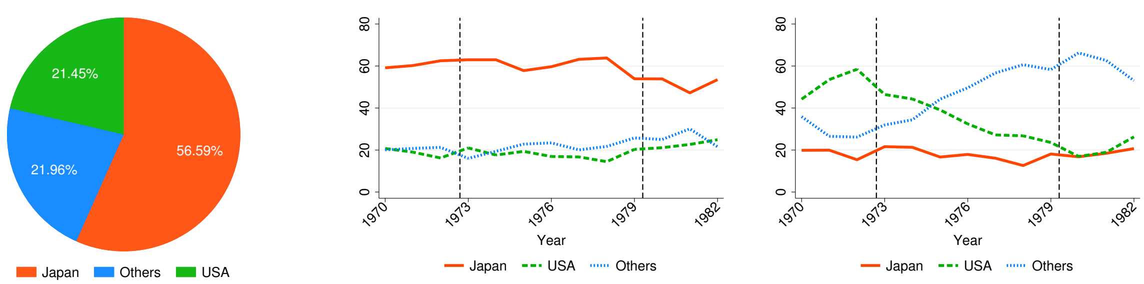
Notes. Panel A displays the mean of log sales for winners and losers, normalized by the average before the event, respectively. Panel B illustrates the sectoral distribution of all contracts and cancellation episodes.

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	1.49	0	2.78	72	1.06	0	2.44	35	0.60	[0.44]
Ihs # cum. citations	1.58	0	2.96	72	1.14	0	2.63	35	0.55	[0.46]
$\mathbb{1}[\#$ cum. patents $\geq 0]$	0.26	0	0.44	72	0.20	0	0.50	35	1.31	[0.48]
$\mathbb{1}[\#$ cum. citations $\geq 0]$	0.26	0	0.44	72	0.20	0	0.50	35	1.31	[0.48]

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.

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 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

	Alternative TFP		Non-missing emp.		Matching # = 2			Matching # = 4			Two-way clustering		
Dep. Var.	Labor prod.	Export dummy	Sale	Subsidy	Sale	TFP^{rr}	Subsidy	Sale	TFP^{rr}	Subsidy	Sale	TFP^{rr}	Subsidy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
4 years before	−0.35	0.07	−0.21	0.07	−0.15	−0.39	0.08	−0.08	−0.33	0.09	−0.08	−0.33	0.09
	(0.45)	(0.15)	(0.20)	(0.09)	(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	−0.08	−0.12	0.05	−0.15	−0.00	0.03	−0.17	−0.01	0.03	−0.17	−0.01
	(0.32)	(0.10)	(0.19)	(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	0.04	0.03	0.07	−0.08	0.03	0.15	−0.09	0.03	0.15	−0.09	0.03
	(0.29)	(0.10)	(0.15)	(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	−0.11	0.08	0.03	−0.04	0.03	0.01	−0.07	0.04	0.01	−0.07	0.04
	(0.15)	(0.08)	(0.10)	(0.12)	(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	0.31	−0.10	0.67*	0.53	0.00	0.53	0.14	0.01	0.53*	0.14	0.01
	(0.46)	(0.19)	(0.26)	(0.11)	(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	1.02**	−0.17	0.84***	0.72*	−0.05	0.96***	0.75*	−0.04	0.96***	0.75*	−0.04
	(0.63)	(0.19)	(0.45)	(0.13)	(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*	0.40	0.04	0.71***	0.25	0.13	0.82**	0.15	0.09	0.82***	0.15	0.09
	(0.28)	(0.19)	(0.24)	(0.20)	(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	0.68**	−0.15	1.00***	0.64**	−0.04	1.18***	0.59**	−0.04	1.18***	0.59*	−0.04
	(0.29)	(0.28)	(0.25)	(0.15)	(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	0.88**	−0.14	1.09**	0.59*	−0.04	1.28***	0.58*	−0.04	1.28**	0.58*	−0.04
	(0.34)	(0.19)	(0.36)	(0.13)	(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	0.74**	−0.10	1.02**	0.91***	−0.05	1.08**	0.86***	−0.05	1.08**	0.86**	−0.05
	(0.43)	(0.18)	(0.32)	(0.16)	(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	1.07**	−0.08	1.05**	0.78***	−0.05	1.11**	0.74***	−0.05	1.11**	0.74**	−0.05
	(0.41)	(0.28)	(0.44)	(0.14)	(0.45)	(0.29)	(0.10)	(0.43)	(0.26)	(0.09)	(0.42)	(0.28)	(0.10)
# Cl. (Firm)	80	91	80	80	82	72	82	95	84	95	95	84	95
# Cl. (Match)											35	33	35
N	484	644	484	484	565	425	565	690	515	690	690	515	690
Match-firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Match-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Standard errors in parenthesis are clustered at the firm level or two-way clustered at the firm and match levels in columns 1-10 or 11-13, 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 3-4, we consider estimation sample with non-missing employment. In columns 5-7 and 8-10, we consider alternative numbers of matched winners of 2 and 4, respectively.

Table B4: Robustness. Direct Effects on Adopters. Average Effects

Dep.	Sale	TFP^{rr}	Subsidy
	(1)	(2)	(3)
$\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]$	0.92^{***}	0.64^{**}	-0.03
	(0.34)	(0.25)	(0.06)
# Cl. (Firm)	91	80	91
N	644	484	644
Match×Firm FE	✓	✓	✓
Match×Year FE	✓	✓	✓

Notes. Standard errors in parentheses are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table reports the estimates from the following regression model: $y_{imt} = \beta(\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]) + \delta_{im} + \delta_{mt} + \epsilon_{imt}$. The dependent variables are log sales, TFP^{rr}, or a dummy variable indicating the receipt of subsidy in columns 1-3, respectively. All specifications control for match-firm and match-year fixed effects.

Table B5: First Stage Regression. Local Spillovers and Complementarity

	Local Spillovers		Local Complementarity	
Dep.	$\triangle\text{Share}_{nj,t-2}$			
	(1)	(2)	(3)	(4)
$\text{IV}^{25\text{km}}_{nj,t-2}$	0.10^{***}	0.10^{***}	0.11^{***}	0.11^{***}
	(0.02)	(0.02)	(0.03)	(0.03)
# Cl. (Region)	79	79	86	86
# Cl. (Group)	1294	1294	1548	1548
N	1492	1492	1977	1977
Full controls		✓		✓
Region FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓

Notes. Standard errors two-way clustered at the region and business group levels are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Columns 1-2, and 3-4 report the first stage regression results of Tables 2 and 3, respectively. Adopter shares and IV are defined in Equations (3.3) and (3.5), respectively. In columns 2 and 4, we include all additional controls including a control for market access defined in Equation (3.6), a control for own region-sector gross output defined in Equation (3.7), the inverse hyperbolic sine transformation of cumulative credit received between 1973 and 1979, an industrial complex dummy, and interaction terms between port dummies and import and input tariffs. All specifications include region, sector, and sector-group fixed effects.

Table B6: Robustness. Local Spillovers. 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)
$\triangle \text{Share}_{nj,t-2}$	0.12		1.75	0.08		-1.19
	(0.34)		(1.46)	(0.14)		(0.85)
$\text{IV}^{25\text{km}\geq}_{nj,t-2}$		0.42			-0.27	
		(0.34)			(0.17)	
KP-F			21.35			21.33
# Cl. (Region)	73	73	73	73	73	73
# Cl. (Group)	830	830	830	830	830	830
N	1004	1004	1004	1004	1004	1004
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓

Notes. Standard errors two-way clustered at the region and business group levels 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 B7: Robustness. Local Spillovers. Firm Entry and Exit

	(1)	(2)	(3)	(4)
$\triangle \text{Share}_{nj,t-2}$	-0.14	-0.11	2.05^{*}	0.53
	(0.11)	(0.07)	(1.16)	(0.85)
KP-F	11.46	5.98	12.63	11.44
# Cl. (Region)	85	90	92	99
# Cl. (Group)	1049	1264	1450	1757
N	1760	2285	2486	3313
Region FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓

Notes. Standard errors two-way clustered at the region and business group levels are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table report the IV estimates of Equation (3.4). Dependent variables are the exit and the entry dummies in columns 1-2 and 3-4, respectively. In columns 1-2 and 3-4, the estimation samples consist of firms operating in 1972 or 1973 and 1979 or 1980, respectively. We consider the never-adopter sample in columns 1 and 3, and the sample including both ever- and never-adopters in columns 2 and 4. All specifications include region, sector, and sector-group fixed effects.

Table B8: Robustness. Functional Form. Local Spillovers

Dep. $\triangle \ln \text{Sales}_{it}$ 1970-1972 or 1973-1980			
	(1)	(2)	(3)
$\triangle \text{Share}_{nj,t-2}$	4.30^{**}	3.74^{***}	3.48^{***}
	(2.15)	(0.95)	(0.77)
$\triangle \text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\text{Share}_{(-i)njt_0} \geq \text{p90}]$	5.35		
	(3.78)		
$\triangle \text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\# \text{ firms}_{njt_0} \geq \text{p90}]$		-2.43	
		(2.45)	
$\triangle \text{Share}_{(-i)nj,t-2} \times \mathbb{1}[\text{Sale}_{it_0} \geq \text{p90}]$			-15.16
			(44.91)
SW-F, Share	10.03	25.62	35.92
SW-F, Interaction	19.02	13.81	45.30
# Cl. (Region)	79	79	79
# Cl. (Group)	1294	1294	1294
N	1492	1492	1492
Region FE	✓	✓	✓
Sector FE	✓	✓	✓
Sector-group FE	✓	✓	✓

Notes. Standard errors in parenthesis are two-way clustered at the region and business group levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the IV estimates of Equation (3.4). In columns 1-3, 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 B9: Robustness. Local Spillovers

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	Non-missing emp.	Full-sample	Baseline			
IV	$IV^{\geq 25km}_{inj,t-2}$			$IV^{\geq 25km}_{inj,t-3}$	$IV^{\geq 25km}_{inj,t-2}$					$IV^{\geq 0km}_{inj,t-2}$	$IV^{\geq 10km}_{inj,t-2}$	$IV^{\geq 50km}_{inj,t-2}$	$IV^{\geq 150km}_{inj,t-2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\triangle \text{Share}_{(-i)nj,t-2}$	1.13**	1.62**	2.48**		3.66***	2.97***	3.90**	4.29***	3.06*	3.66***	4.04***	3.61***	3.73***
	(0.43)	(0.69)	(1.05)		(0.94)	(0.82)	(1.79)	(1.32)	(1.74)	(1.03)	(1.16)	(1.00)	(1.03)
$\triangle \text{Share}_{(-i)nj,t-3}$				2.61***									
				(0.65)									
KP-F	30.92	29.62	30.83	57.03	30.98	20.84	10.64	26.37	11.36	34.47	28.80	26.64	30.56
# Cl. (Region)	79	67	79	79	79	76	62	67	86	79	79	79	79
# Cl. (Group)	1294	742	1294	1294	1221	999	724	742	1548	1294	1294	1294	1294
N	1492	824	1492	1492	1360	1117	734	824	1977	1492	1492	1492	1492
Region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Initial y_{it_0}	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Standard errors in parenthesis are two-way clustered at the region and business group levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the IV estimates of Equation (3.4). In column 1, 2, and 3-13, 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 10-13. 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; the sample with non-missing employment in column 8; and the full-sample including both never- and ever-adopters in column 9. In columns 10-13, 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 B10: 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)
$\triangle\text{Share}_{(-i)nj,t-2}$		0.57**	0.62**	1.06**	0.66**	0.68**	0.65**	0.61**
		(0.24)	(0.26)	(0.52)	(0.30)	(0.32)	(0.27)	(0.26)
$\triangle\text{Share}_{(-i)nj,t-3}$	0.25***							
	(0.08)							
KP-F	56.95	10.89	12.09	4.83	11.15	9.86	12.96	11.51
# 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
Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector-group FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes. Standard errors in parenthesis are two-way clustered at the region and business group levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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

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

Note that $\frac{L_t}{Q_t} = \frac{\int l_{it} \mathrm{d}i}{Q_t} = \int \frac{y_{it}}{Q}\frac{1}{z_{it}}\mathrm{d}i = \int \frac{1}{z_{it}}\big(\frac{p_{it}}{P_t}\big)^{-\sigma}\mathrm{d}i$ holds, where $z_{it} = \eta f(\lambda_{t-1}^T)\phi_{it}$ for adopters and $z_{it} = f(\lambda_{t-1}^T)\phi_{it}$ for non-adopters. Using that $p_{it} = \frac{\mu w_t}{z_{it}}$ and $P_t = \mu w_t [\int z_{it}^{\sigma-1}\mathrm{d}i]^{\frac{1}{1-\sigma}}$, we obtain $Q_t = [\int z_{it}^{\sigma-1}\mathrm{d}i]^{\frac{1}{\sigma-1}}$. From the assumption of Pareto distribution, we can further derive that

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

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

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

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

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

Let $\hat{\lambda}_t^T$ be the solution of Equation (C.4). Note that given λ_{t-1}^T, $\hat{\lambda}_t^T$ is uniquely determined by Equation (C.4) because the left hand side is strictly increasing in λ_t^T and the right hand side is strictly decreasing in λ_t^T due to that $\sigma > 2$ (Assumption 1(i)). Because the equilibrium share is bounded by 1, the equilibrium share is determined as follows:

$$\lambda_t^T = \begin{cases} \hat{\lambda}_t^T & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T) \frac{\eta^{\sigma-1}-1}{\sigma F^T} < 1 \\ 1 & \text{if} \quad A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T) \frac{\eta^{\sigma-1}-1}{\sigma F^T} \geq 1. \end{cases} \tag{C.5}$$

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(i), there exists a unique value of $\hat{\lambda}_t^T$ that satisfies this equation. If the obtained $\hat{\lambda}_t^T$ from this equation is greater than 1, because the equilibrium share is bounded by 1, $\lambda_t^T = 1$. Therefore, given λ_{t-1}^T, there exists a unique equilibrium share λ_t^T each period, which forms a unique dynamic equilibrium path given an initial share $\lambda_{t_0}^T$.

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

$$G(\hat{\lambda}_t^T; \eta, \delta, \lambda_{t-1}^T) = A(\hat{\lambda}_t^T)^{2-\sigma} f(\lambda_{t-1}^T) \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} - (\hat{\lambda}_t^T)^{\frac{\sigma-1}{\theta}} = 0. \tag{C.6}$$

Taking the derivative of Equation (C.6) with respect to λ_t^T, we obtain

$$\frac{\partial G}{\partial \hat{\lambda}_t^T} = \underbrace{\frac{2-\sigma}{\sigma-1}}_{<0} \times \underbrace{A(\hat{\lambda}_t^T)^{3-2\sigma}(\hat{\lambda}_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T) \frac{(\eta^{\sigma-1}-1)^2}{\sigma F^T}}_{>0} - \underbrace{\frac{\sigma-1}{\theta}(\hat{\lambda}_t^T)^{-\frac{\tilde{\theta}}{\theta}}}_{>0} < 0, \tag{C.7}$$

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

$$\frac{\partial G}{\partial \lambda_{t-1}^T} = A(\hat{\lambda}_t^T)^{2-\sigma} \frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda_{t-1}^T)\delta > 0. \tag{C.8}$$

Applying the implicit function theorem and using the signs of Equations (C.7) and (C.8), we obtain $\frac{\partial \hat{\lambda}_t^T}{\partial \lambda_{t-1}^T} = -\frac{\partial G/\partial \lambda_{t-1}^T}{\partial G/\partial \hat{\lambda}_t^T} > 0$. Therefore, $\frac{\partial \lambda_t^T}{\partial \lambda_{t-1}^T} > 0$ holds for the equilibrium λ_t^T with the value lower than 1 (non-boundary solutions of Equation (C.5) that satisfy $\hat{\lambda}_t^T = \lambda_t^T$) and the equality holds for the equilibrium λ_t^T that takes the value of 1 (boundary solutions of Equation (C.5)).

Proposition 1(iii) Taking the derivative of Equation (C.6) with respect to η and δ, we obtain

$$\frac{\partial G}{\partial \eta} = A(\hat{\lambda}_t^T)^{3-2\sigma} f(\lambda_{t-1}^T) \frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T} \frac{\theta}{\tilde{\theta}} \left[\frac{1}{\sigma-1}(\eta^{\sigma-1}-1)(\hat{\lambda}_t^T)^{\frac{\tilde{\theta}}{\theta}} + 1 \right] > 0, \tag{C.9}$$

and

$$\frac{\partial G}{\partial \delta} = A(\hat{\lambda}_t^T)^{2-\sigma} \frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda_{t-1}^T)\lambda_{t-1}^T > 0, \tag{C.10}$$

respectively. Applying the implicit function theorem and using the signs of Equations (C.7), (C.10), and (C.9), we obtain $\frac{\partial \hat{\lambda}_t^T}{\partial \eta} = -\frac{\partial G/\partial \eta}{\partial G/\partial \hat{\lambda}_t^T} > 0$ and $\frac{\partial \hat{\lambda}_t^T}{\partial \delta} = -\frac{\partial G/\partial \delta}{\partial G/\partial \hat{\lambda}_t^T} > 0$. Therefore, $\frac{\partial \hat{\lambda}_t^T}{\partial \eta} \geq 0$ and $\frac{\partial \hat{\lambda}_t^T}{\partial \delta} \geq 0$ hold strictly for the non-boundary solutions and as equality for the boundary solutions of Equation (C.5).

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

$$\frac{\partial^2 \hat{\lambda}_t^T}{\partial(\lambda_{t-1}^T)^2} = \frac{-1}{(\partial G/\partial \hat{\lambda}_t^T)^3}\left[\frac{\partial G^2}{\partial(\lambda_{t-1}^T)^2}\left(\frac{\partial G}{\partial \hat{\lambda}_t^T}\right)^2 - 2\frac{\partial^2 G}{\partial \hat{\lambda}_t^T \partial \lambda_{t-1}^T}\frac{\partial G}{\partial \lambda_{t-1}^T}\frac{\partial G}{\partial \hat{\lambda}_t^T} + \frac{\partial^2 G}{\partial(\hat{\lambda}_t^T)^2}\left(\frac{\partial G}{\partial \lambda_{t-1}^T}\right)^2\right]. \quad \text{(C.11)}$$

We examine the sign of each term of the right hand side of the above equation.

$$\frac{\partial^2 G}{\partial(\lambda_{t-1}^T)^2} = A(\hat{\lambda}_t^T)^{2-\sigma}\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda_{t-1}^T)\delta^2 > 0. \quad \text{(C.12)}$$

$$\frac{\partial^2 G}{\partial \hat{\lambda}_t^T \partial \lambda_{t-1}^T} = \frac{\partial^2 G}{\partial \lambda_{t-1}^T \partial \hat{\lambda}_t^T} = \underbrace{\frac{2-\sigma}{\sigma-1}}_{<0}\underbrace{A(\hat{\lambda}_t^T)^{3-2\sigma}(\eta^{\sigma-1}-1)(\hat{\lambda}_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T)\delta}_{>0} < 0. \quad \text{(C.13)}$$

$$\begin{aligned}\frac{\partial^2 G}{\partial(\hat{\lambda}_t^T)^2} = {} & \underbrace{\frac{(2-\sigma)(3-\sigma)}{(\sigma-1)^2}}_{>0}\underbrace{A(\hat{\lambda}_t^T)^{4-3\sigma}(\hat{\lambda}_t^T)^{-\frac{2(\sigma-1)}{\theta}}(\eta^{\sigma-1}-1)f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)^3}{\sigma F^T}}_{>0} \\ & + \underbrace{\frac{\sigma-2}{\theta}A(\hat{\lambda}_t^T)^{3-2\sigma}(\hat{\lambda}_t^T)^{-\frac{\sigma-1}{\theta}-1}f(\lambda_{t-1}^T)\frac{(\eta^{\sigma-1}-1)^2}{\sigma F^T}}_{>0} + \underbrace{\frac{\sigma-1}{\theta}\frac{\tilde{\theta}}{\theta}(\hat{\lambda}_t^T)^{-\frac{\tilde{\theta}}{\theta}-1}}_{>0} > 0, \end{aligned} \quad \text{(C.14)}$$

where each term of the right hand side of Equation (C.14) is positive due to that $\sigma > 3$. Substituting the signs of Equations (C.7), (C.8), (C.12), (C.13), and (C.14) into Equation (C.11), we obtain $\frac{\partial^2 \hat{\lambda}_t^T}{\partial(\lambda_{t-1}^T)^2} > 0$, which proves the strict convexity.

Because the intercept of λ_t^T-axis is always positive and $\hat{\lambda}_t^T$ 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 $\hat{\lambda}_t^T$ strictly increases in δ, there exists $\underline{\delta}$ such that the 45-degree line and the short-run locus meet at $\lambda_{t-1}^T = 1$, holding other parameters constant; that is, $\underline{\delta}$ satisfies $A(\hat{\lambda}^T;\eta)^{2-\sigma} f(\hat{\lambda}^T;\underline{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - \hat{\lambda}^T = 0$ for $\hat{\lambda}^T = 1$. Similarly, holding other parameters constant, there exists $\underline{\eta}$ that satisfies $A(\hat{\lambda}^T;\underline{\eta})^{2-\sigma} f(\hat{\lambda}^T;\delta)\frac{(\underline{\eta}^{\sigma-1}-1)}{\sigma F^T} - \hat{\lambda}^T = 0$ for $\hat{\lambda}^T = 1$. Also, because $\hat{\lambda}_t^T$ is strictly convex in λ_{t-1}^T, holding other parameters constant, 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.6); that is, $\bar{\delta}$ and $\bar{\eta}$ satisfy $A(\hat{\lambda}^T;\eta)^{2-\sigma} f(\hat{\lambda}^T;\bar{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T} - \hat{\lambda}^T = 0$ and $A(\hat{\lambda}^T;\bar{\eta})^{2-\sigma} f(\hat{\lambda}^T;\delta)\frac{(\bar{\eta}^{\sigma-1}-1)}{\sigma F^T} - \hat{\lambda}^T = 0$ for some value $\hat{\lambda}^T$, respectively.

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) intersect with the 45-degree line only once. For $\delta \in (\bar{\delta}, 1]$ or $\eta \in (\bar{\eta}, 1]$, the short-run locus intersects with the 45-degree line at $\lambda^T = \lambda_t^T = \lambda_{t-1}^T = 1$ only once.

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 $\delta \in \{\underline{\delta}, \bar{\delta}\}$ or $\eta \in \{\underline{\eta}, \bar{\eta}\}$, the short-run locus and the 45-degree line intersect 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. Note that

$$\frac{\Pi_t}{P_t} = \frac{1}{P_t}\int \frac{1}{\sigma}\left(\frac{\mu w_t}{z_{it}}\right)^{1-\sigma} P_t^{\sigma} Q_t \mathrm{d}i = \frac{1}{\sigma}\mu^{1-\sigma}\left(\frac{w_t}{P_t}\right)^{1-\sigma}\left[\int z_{it}^{\sigma-1}\mathrm{d}i\right] Q_t = \frac{1}{\sigma}A(\lambda_t^T)f(\lambda_{t-1}^T),$$

where the last equality comes from Equations (C.2) and (C.3). The above equation implies that welfare in each period $\frac{w_t+\Pi_t}{P_t}$ is equal to $f(\lambda_{t-1}^T)A(\lambda_t^T)$ and welfare in a steady state is $f(\lambda^T)A(\lambda^T)$, which strictly increases in λ^T. Therefore, a steady state with a larger adopter share Pareto-dominates others with lower shares.

Proposition 2 Suppose an economy features multiple steady states S^{Pre}, S^{U}, and S^{Ind} and is initially stuck in the poverty trap, $\lambda_{t_0} \in [0, S^{\mathrm{U}})$.

We first consider input subsidies for adopters. With the subsidies, firms' costs of production become $(1-s_{it})w_t l_{it}$ where $s_{it} = \bar{s}_t$ for $T_{it} = 1$ and 0 otherwise, where $0 < \bar{s}_t < 1$ is the subsidy rate for adopters. Firm charges price $p_{it} = \frac{\mu(1-s_{it})w_t}{z_{it}}$. The cutoff is

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

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

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

The equilibrium share of adopters can be expressed as

$$\lambda_t^T = \left[\frac{\left(\frac{\eta}{1-\bar{s}_t}\right)^{\sigma-1} - 1}{\sigma F^T} A(\lambda_t^T)\tilde{A}(\lambda_t^T, \bar{s}_t)^{1-\sigma} f(\lambda_{t-1}^T)\right]^{\frac{\theta}{\sigma-1}}. \tag{C.15}$$

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

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

The equilibrium adopter shares are

$$\lambda_t^T = \left[\frac{\eta^{\sigma-1} - 1}{\sigma(1-\bar{s}_t)F^T} A(\lambda_t^T)^{2-\sigma} f(\lambda_{t-1}^T)\right]^{\frac{\theta}{\sigma-1}}. \tag{C.16}$$

In the cases of both subsidies, the right hand sides of both Equations (C.15) and (C.16) strictly increase in $\bar{s}_t$, and $\lim_{\bar{s}_t \to 1} \lambda_t^T \to 1$. Therefore, there exists $\underline{s}$ such that satisfies $\lambda_t^T = S^{\mathrm{U}}$. For $\bar{s}_t > \underline{s}$, $\lambda_t^T > S^{\mathrm{U}}$ 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 values of L_t. In such a case, the cutoff and equilibrium shares are determined as

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

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 closed economy setup with one sector and one region as in Section 4.

Local diffusion of knowledge A firm receives exogenous productivity $\tilde{\phi}_{it}$ and makes two static decisions in 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

$$\pi_{it} = \max_{T_{it}\in\{0,1\}, a_{it}\in[0,\infty)} \left\{ \frac{1}{\sigma}\left(\frac{\mu w_t}{\tilde{\eta}^{T_{it}} a_{it}^{\gamma_1} \tilde{\phi}_{it}}\right)^{1-\sigma} P_t^{\sigma} Q_t - T_{it} P_t F^T - w_t a_{it}^{\alpha_1} g(\lambda_{t-1}^T) P_t^{\sigma} Q_t \right\}, \tag{C.17}$$

where $\tilde{\eta}$ governs direct productivity gains from the adoption, and $a_{it}^{\alpha_1} g(\lambda_{t-1}^T) P_t^{\sigma} Q_t$ is the cost of innovation in units of labor. The cost of innovation is proportional to market size $P_t^{\sigma} Q_t$ and increases in a_{it} because $\alpha_1 > 0$. We normalize $w_t = 1$ without loss of generality.

The positive externalities of technology adoption come from that the innovation costs are decreasing in the previous adopter share $\partial g(\lambda_{t-1}^T)/\partial \lambda_{t-1}^T < 0$. This captures that with a higher share, other local firms are more likely to learn new ideas from these adopters and use this knowledge for their own innovation. We impose that $\tilde{\alpha} = \alpha_1 - \gamma_1(\sigma - 1) > 0$, 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

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

Because $-1/\tilde{\alpha} > 0$ and $(\sigma-1)/\tilde{\alpha} > 0$, a_{it} increases in λ^T_{t-1}, T_{it}, and $\tilde{\phi}_{it}$. Substituting the optimal a_{it} into Equation (C.17), a firm's maximization problem can be re-written as:

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

where $\bar{C}$ is a collection of model parameters. $g(\lambda^T_{n,t-1})^{-\frac{\gamma_1}{\tilde{\alpha}}}$ can be mapped to $f(\lambda^T_{n,t-1})$, $(\tilde{\phi}_{it})^{\frac{\alpha_1}{\tilde{\alpha}}}$ to ϕ_{it}, and $\tilde{\eta}^{\frac{\alpha_1}{\tilde{\alpha}_1}}$ to η in Section 4.

Learning externalities and labor mobility There is a unit measure of engineers and owners of firms. 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 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 λ^T_{t-1} and $1-\lambda^T_{t-1}$, respectively.

A firm's maximization problem is

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

This can be re-written as

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

where $\tilde{f}(\lambda^T_{t-1}) = [\lambda^T_{t-1}(\gamma_1^{\sigma-1} - 1) + 1]^{\frac{1}{\sigma-1}}$ can be mapped to $f(\lambda^T_{t-1})$ in Section 4.

Appendix D Quantitative Model

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

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

where q_{imnjt} and q^f_{njt} are region n's quantities demanded of a variety produced by domestic firm i located in region m and foreign firms, respectively.

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

$$c_{njt} = \left(\frac{w_{nt}}{\gamma^L_j}\right)^{\gamma^L_j} \prod_k \left(\frac{P_{nkt}}{\gamma^k_j}\right)^{\gamma^k_j}.$$

Firm i's quantities demanded from region m and Foreign are $q_{inmjt} = (p_{inmjt})^{-\sigma} P^{\sigma}_{mjt} Q_{mjt}$ and $q^x_{injt} = (p^x_{injt})^{-\sigma} D^x_{jt}$, respectively. 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}:

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

where x_{it} is a binary export decision. $\pi^m(T_{it}; \phi_{it})$ are operating profits conditional on adoption status obtained from region m, and $\pi^d(T_{it}; \phi_{it}) = \sum_m \pi^m(T_{it}; \phi_{it})$ 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:

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

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

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

A share of adopters is expressed as

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

where $G_{njt}(\phi)$ is productivity distribution of region-sector nj in period 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

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

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:

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

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

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

Region n's share of the total sector j expenditure on goods from domestic region m and from Foreign are expressed as $\pi_{mnjt} = \left(\frac{\tau_{mnj} c_{mjt}/\bar{\phi}^{\text{avg}}_{mjt}}{P_{njt}}\right)^{1-\sigma}$ and $\pi^f_{njt} = \left(\frac{\tau^x_{nj}(1+t_{jt})P^f_{jt}}{P_{njt}}\right)^{1-\sigma}$. Regional gross output for domestic expenditures R^d_{njt} and the total value of exports R^x_{njt} are

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

The total regional gross output is $R_{njt} = R^d_{njt} + R^x_{njt}$.

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

$$w_{nt} L_{nt} = \left[\sum_j \gamma^L_j \left(\frac{1}{\mu} R_{njt} + M^T_{njt} c_{njt} F^T_{nj}\right) + M^x_{njt} w_{nt} F^x_j\right], \tag{D.2}$$

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

$$R^d_{njt} = \sum_m \pi_{nmjt}(\alpha_j w_{nt} L_{nt} + \gamma^j_k \frac{1}{\mu} R_{nkt} + \gamma^j_k M^T_{njt} c_{njt} F^T_{nj}). \tag{D.3}$$

The government budget is balanced each period:

$$\sum_{n,j} \frac{t_{jt}}{1+t_{jt}} \pi^f_{njt} P_{njt} Q_{njt} + \tau^w_t \sum_n w_{nt} L_{nt} = \sum_{n,j} \left[\frac{s_{njt}}{1-s_{njt}} M_{nj} \int_{\bar{\phi}^T_{njt}}^{\kappa \phi^{\min}_{njt}} \frac{1}{\mu} r(\phi_{it}) dG_{njt}(\phi)\right], \tag{D.4}$$

where the left-hand side is sum of government revenues from import 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 $\{p_{inmjt}, q_{inmjt}, p^x_{injt}, q^x_{injt}, T_{it}, x_{it}\}$, 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; (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 $\{L^{\text{Data}}_{n,68}\}_{n\in\mathcal{N}}$ in 1968
2. Region-sector gross output $\{R^{\text{Data}}_{njt}\}_{n\in\mathcal{N}, j\in\mathcal{J}, t\in\{72,76,80\}}$

3. Population $\{L_{nt}^{\text{Data}}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$
4. Sectoral exports and import shares $\{\text{EX}_{jt}^{\text{Data}}, \pi_{jt}^{f,\text{Data}}\}_{j\in\mathcal{J},t\in\{72,76,80\}}$
5. Import tariffs $\{t_{jt}\}_{j\in\mathcal{J},t\in\{72,76,80\}}$

Algorithm Taking the values of $\mathbf{\Theta}^{\text{E}}$ and data inputs as given, we obtain the values of $\mathbf{\Theta}^{\text{M}}$, $\bar{s}$, 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 $\{\mathbf{\Theta}^{\text{M}}, \bar{s}\}$, 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 solving for the constraints of the minimization problem.
   (a) Update $\{D_{jt}^{f'}\}$ by fitting the export intensities of the model to those in the data $\frac{\text{EX}_{jt}^{\text{Data}}}{\sum_n R_{njt}^{\text{Data}}}$.
   (b) Update $\{P_{jt}^{F'}\}$ by fitting the import shares of the model to those in the data $\pi_{jt}^{f,\text{Data}}$.
   (c) Update $\{V_{nt}'\}$ until the population outcome of the model matches the actual distribution of the population L_{nt}^{Data}. 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 $\frac{GO_{njt}^{\text{Data}}}{\sum_{m,k} GO_{mkt}^{\text{Data}}}$. Within each sector, the regional gross output distribution 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 $\{\hat{\mathbf{\Theta}}^{\text{M}}, \hat{\mathbf{s}}_t\}$ that minimize the objective function.