Industrialization and the Big Push: Theory and Evidence from South Korea*

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Abstract

We study how one-time subsidies for adoption of modern technology drove South Korea's industrialization in the 1970s. Leveraging unique historical data, we provide causal evidence consistent with coordination failures: adoption improved adopters' performance and generated local spillovers, with firms more likely to adopt when other local firms had already adopted. We incorporate these findings into a quantitative model, where the potential for multiple steady states depends on parameters mapped to the causal estimates. In our calibrated model, South Korea's one-time subsidies shifted its economy to a more industrialized steady state, increasing heavy manufacturing's GDP share by 8.6% and export intensity by 16.2%. Larger market access amplifies the effects of these subsidies, as the gains from adoption increase with firms' scale.

Keywords: big push, industrialization, coordination failure, complementarity, local spillover, market access
JEL Codes: O14, O25, R11

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1. Introduction

Since Rosenstein-Rodan (1943) and Hirschman (1958), coordination failures in adoption of modern technology have been hypothesized as significant barriers for economic development. In the presence of such failures, a one-time "big push" policy intervention could potentially resolve these failures, permanently shifting an economy to a fundamentally better steady state. Despite its theoretical appeal, the real-world relevance of the big push remains underexplored, with skepticism often arising from a lack of quantification grounded in credible evidence.

This paper empirically and quantitatively examines the possibility of industrialization through a big push for technology adoption. Our analysis focuses on South Korea's large-scale policy, implemented between 1973 and 1979, that temporarily subsidized adoption of modern technology in heavy manufacturing sectors. This period is notable, because South Korea began experiencing rapid industrialization during this relatively short implementation window.

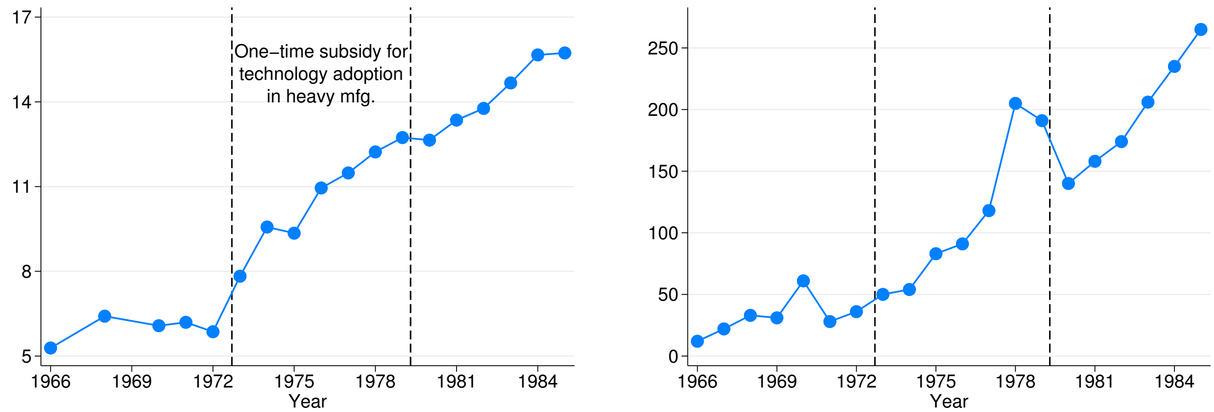
Our main contributions are twofold. First, using novel historical microdata, we provide causal evidence on the firm-level effects of technology adoption, which align with coordination failures and the big push hypothesis. We estimate direct effects of adoption on adopters and local spillovers on non-adopters. Additionally, we provide evidence of local complementarity: firms are more likely to adopt when other local firms have already adopted. Second, we develop a quantitative model, in which key parameters—determining the presence of the multiplicity—are tightly pinned down by the empirical estimates. In this calibrated model, without South Korea's big push policy, the economy would have converged to an alternative, less-industrialized steady state. Moreover, larger internal and international market access played a significant role in amplifying the effects of the big push.

Our dataset covers the universe of technology adoption contracts between South Korean and foreign firms from 1970 to 1982. Given South Korea's technological gap with respect to the global frontier, foreign sources were the most important channel for acquiring modern technologies. The dataset was manually constructed by digitizing contract documents that firms were required to file with government authorities. In our context, technology adoption refers to transfers of industrial know-how, defined as transfers of blueprints or provision of training services, aimed at facilitating mass industrial production.

As shown in Figure 1, the dataset reveals a novel pattern consistent with the big push hypothesis. Only after the policy was implemented did the share of the heavy manufacturing sectors in GDP begin to rise, increasing from 6% to 13% during the policy period. This was accompanied by a significant influx of new technologies through adoption contracts with foreign firms, resulting in fourfold increases in the number of new contracts in these sectors. Even after the policy ended, the economy continued to specialize in the heavy manufacturing sectors. Appendix Figure B1 shows similar patterns for employment and exports.

Using this novel dataset, we present three main empirical findings on the firm-level effects of technology adoption. The first finding is the direct effects on adopters. To address the empirical

Figure 1: Big Push, Adoption of Modern Technology, and Industrialization in South Korea



A. Heavy mfg. share of GDP (%)

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

Notes. The two dotted vertical lines indicate the start and end of the South Korean government's big push, which temporarily subsidized adoption of modern technologies from foreign firms in heavy manufacturing sectors from 1973 to 1979. Heavy manufacturing sectors include chemicals, electronics, machinery, steel, non-ferrous metal, and transportation equipment. We obtain sectoral value-added data from the Bank of Korea's input-output tables for the pre-1970 period and from the OECD STAN database for the post-1970 period. The adoption contract data come from our own digitized dataset, constructed from historical archives, as detailed in Section 2.2. Appendix Figure B1 presents similar patterns for heavy manufacturing employment and exports.

challenge of selection bias, we use a winners vs. losers research design. We compare firms that successfully adopted technology ("winners") with firms that initially signed contracts with foreign firms but ultimately *failed* or were *delayed* in adopting technology because the foreign firms canceled the contracts due to circumstances plausibly exogenous to these Korean firms ("losers"). We match each loser to observationally similar winners. Using these matches, we use a stacked-by-event design, where treatment effects are estimated based on comparisons between winners and never-treated or not-yet-treated losers. Our results show that technology adoption increased winners' sales by 91% and revenue total factor productivity (TFP) by 94%.

Our second finding is local spillovers from adoption. We regress growth in sales or revenue TFP on changes in local region-sector level adopter shares. The key identification challenge is that more firms may adopt technology in certain regions due to local unobservables that could simultaneously influence firm growth. To address this endogeneity, we propose an IV strategy based on spatial networks of business groups with multiple firms across regions, using group-level technology adoption decisions as exogenous shifters for adopter shares in focal regions where the group initially owned firms. Our estimates indicate that a 1 percentage point increase in adopter shares led to 2.7% and 1.6% higher sales and revenue TFP for non-adopters, respectively.

The third finding is the presence of local complementarity in adoption, where higher adopter shares lead to more adoption at the local level. Using the same IV strategy, we regress a dummy for technology adoption on local adopter shares. We find that a 1 percentage point increase in adopter shares led to a 0.85 percentage point higher probability of adopting new technologies, about 14% of the average annual adoption probability in 1979, when the policy ended. The magnitude of this complementarity was more pronounced in regions with larger market access.

These three findings align with the big push narrative. Despite seemingly large private returns from adoption—illustrated by the first finding on direct gains—the third finding on local complementarity suggests that firms were less likely to adopt unless other local firms had already adopted, indicating coordination failures. Furthermore, the second finding on local spillovers points to potential positive externalities from adoption, suggesting that private returns alone may not be sufficient to resolve these coordination failures.

Motivated by these results, we develop a simple model that incorporates firms' technology adoption decisions and spillovers from adoption. Firms can adopt more productive modern technologies after incurring fixed adoption costs. Spillovers operate with a one-period lag, where current productivity increases with the adopter shares in the previous period. This lag introduces dynamics into the model, making adopter shares a time-varying state variable.

In this simple model, we derive three main analytical results. First, the model features dynamic complementarity in firms' adoption decisions: higher adopter shares in the previous period lead to higher shares in the current period. This complementarity arises from a combination of spillovers and fixed adoption costs in units of final goods. Larger spillovers from higher adopter shares reduce adoption costs in the following period, encouraging more firms to adopt modern technology. If either condition is not satisfied, the model fails to exhibit the complementarity and cannot reproduce the third empirical finding.

Second, the model rationalizes the possibility of a big push. Dynamic complementarity can lead to multiple steady states: a "pre-industrialized" state with low adopter shares, and an "industrialized" state with high adopter shares. The economy's long-run outcomes depend on initial conditions, indicating path dependence, where temporary events can permanently shape the long-run outcomes. A big push, that provides a one-time subsidy for adoption, can have permanent effects by shifting the economy away from initial conditions that would otherwise lead to the pre-industrialized state. Moreover, because larger market access increases firms' scale and the gains from adoption, a big push is more likely to occur with larger market access.

Third, we do not impose the existence of multiple steady states a priori; they arise only when the two parameters—governing direct gains and spillovers—fall within medium ranges. This implies that for multiple steady states to emerge, private returns from adoption and spillovers must neither be too strong nor too weak. Therefore, the possibility of the big push becomes a quantitative question, with values of these parameters serving as essential preconditions for its success.

For quantitative analysis, we extend the simple model to incorporate costly internal and international trade, as well as input-output linkages across multi-sectors. We calibrate the model using firm-level and regional data. By deriving regression specifications from the model consistent with our empirical analysis, we can tightly map the two key parameters that determine the existence of multiple steady states to the reduced-form empirical estimates. We calibrate the remaining parameters through indirect inference. The calibrated model successfully matches both targeted and non-targeted moments. Notably, as non-targeted moments, the model captures systematic relationships between regional levels of adoption and various measures of market access observed in the data. Matching these moments is crucial, as market access influences the strength of complementarity, as shown in the third empirical finding.

Subsidies are calibrated through indirect inference by matching the increase in average adopter shares across regions during the policy periods compared to the pre-policy levels. Because subsidies were only provided during the policy periods, these moments identify the subsidy levels. The calibrated subsidy rate implies that adopters are subsidized with 8.1% of their input expenditures. On average, about 1.4% of GDP is spent on these subsidies during the policy periods.

Using the calibrated model, we evaluate how South Korea's industrialization trajectory would have evolved without the big push. We compare a counterfactual economy without subsidies to the baseline with subsidies. Without the big push, South Korea would have converged to a less-industrialized steady state, with the heavy manufacturing sector's GDP share and export intensity (exports-to-gross-output ratio) being 8.6% and 16.2% lower, respectively, than in the baseline steady state. The big push modestly raised aggregate welfare by 1.27% but led to uneven regional gains, ranging from −1.44% to 37.52%. These uneven gains are attributable to two opposing forces: while productivity gains in a few regions boosted welfare elsewhere by lowering prices through internal trade linkages, they also intensified domestic competition, reducing profits in other regions.

The effects of the big push are amplified by several factors—related to market access—that increase firm scale. We explore three hypothetical scenarios where these factors are temporarily adjusted to reduce firm scale only during the policy periods while their post-1980 levels remain unchanged. First, instead of allowing foreign demand to grow, we assume it remains constant at its initial level. Second, we implement a protectionist tariff scheme, increasing import tariff rates by 40%—opposite to the 40% reduction observed in the data, which increases costs of imported intermediates. Third, we simulate the absence of transportation improvements by undoing the 66% reduction in travel times due to highway construction in 1970, which increases internal trade costs. In each scenario, subsidies result in different steady states but have weaker effects than the baseline, with lower foreign demand having the greatest impact. In the extreme case where all three scenarios are combined, the big push does not occur, even with subsidies. These results highlight the importance of market access and complementary policies in driving the success of the big push.

We also explore three alternative policy schemes to understand more effective ways to achieve the big push. First, we consider randomizing the regions that receive subsidies. When subsidies are allocated in regions with lower market access, the big push is unlikely to occur, further emphasizing the role of market access. Second, we consider providing general subsidies to all firms, regardless of their adoption status. These general subsidies do not generate the big push, highlighting the need for subsidies to address coordination failures rather than simply distributing funds without targeted goals. Finally, we numerically search for the optimal subsidy rate that maximizes aggregate welfare, finding that it exceeds the baseline rate and results in a steady state with even higher heavy manufacturing GDP shares than the steady state achieved under the baseline rate.

Related literature. Our paper contributes to the literature on the big push, coordination failures, and economic development (e.g., Rosenstein-Rodan, 1943; Hirschman, 1958; Murphy et al., 1989; Matsuyama, 1995; Rodríguez-Clare, 1996; Herrendorf et al., 2000; Ciccone, 2002; Davis and Weinstein, 2002; Redding et al., 2011; Kline and Moretti, 2014; Diodato et al., 2022; Alvarez et al., 2023; Crouzet et al., 2023; Hornbeck et al., 2024). Our main contribution is the quantification of South Korea's actual big push episode using a structural model with parameters disciplined by causal evidence. Our model is most closely related to Buera et al. (2021), who study complementarity in technology adoption and its interaction with distortions. Theoretically, we extend their model to an open economy with multiple regions, where the complementarity arises from local spillovers, and where larger market access amplifies the effects of the big push. Empirically and quantitatively, we use novel firm-level data on technology adoption to analyze the actual big push episode and calibrate the model's parameters—critical preconditions for the existence of multiple steady states—to the causal estimates.

There is a large literature that examines rationales and impacts of industrial policy, including recent empirical studies using diff-in-diff designs (e.g., Juhász, 2018; Giorcelli, 2019; Rotemberg, 2019; Bai et al., 2020; Fan and Zou, 2021; Manelici and Pantea, 2021; Giorcelli and Li, 2023) and theoretical work on optimal policies under financial frictions (Itskhoki and Moll, 2019; Liu, 2019). However, there are relatively few studies that integrate theory and data. Exceptions include Lashkaripour and Lugovskyy (2023) and Bartelme et al. (forthcoming) who quantify optimal industry policies under monopolistic competition and Marshallian externality, respectively, using novel empirical strategies to estimate scale elasticities. Similar to these studies, our paper bridges theory and data by combining a structural model with causal estimates. However, we explore coordination failures and the big push as rationales for industrial policy, with a focus on a specific episode.

In the South Korean context, three recent papers—Lane (forthcoming), Kim et al. (2021), and Choi and Levchenko (2024)—study persistent effects of South Korea's temporary industrial policy at the sector- or firm-level. Unlike these studies, our analysis focuses specifically on the policy's technology adoption channel. Our findings suggest that the big push may explain the persistent effects documented by these papers. Building on the dataset constructed for this study, in our separate work, Choi and Shim (2023) examine the benefits and costs of technology adoption versus innovation across Korea's development stages, focusing on the post-1980 period when innovation became more prominent. In contrast, this paper focuses on Korea's industrialization and the big push of the 1970s.

The paper is also closely connected to the literature on dynamic models of trade, growth, and economic geography (e.g., Desmet and Rossi-Hansberg, 2014; Desmet et al., 2018; Arkolakis et al., 2019; Cai et al., 2022; Giannone, 2021; Peters, 2022; Arkolakis and Walsh, 2023; Eckert and Peters, 2023; Fan et al., 2023; Farrokhi and Pellegrina, 2023; Lind and Ramondo, 2023; Sampson, 2023; Walsh, 2023; Atkin et al., 2024; Eckert et al., 2024; Ellingsen, 2024; Farrokhi et al., 2024; Pellegrina and Sotelo, 2024). 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 (2020) with local productivity endogenously evolving due to technology adoption. Using this model, we examine how internal and international market access interact with the big push.

Structure. The rest of this paper is structured as follows. Section 2 describes the historical background and the data. Section 3 presents the empirical findings. Section 4 presents the simple model that analytically characterizes the potential for the big push. Section 5 details the quantitative model and calibration procedure. Section 6 presents the counterfactual results. Section 7 concludes.

2. Historical Background and Data

2.1 Big Push Episode in South Korea

Motivation of the Policy. In late 1972, the Korean government launched the Heavy and Chemical Industry (HCI) Drive to modernize and expand heavy manufacturing sectors, including chemicals, electronics, machinery, steel, non-ferrous metal, and transportation equipment. The timing and selection of targeted sectors were politically motivated (Kim et al., 2021). President Park narrowly secured his third presidential term in 1971 amid accusations of electoral manipulation, and in October 1972, he formalized his dictatorship, suspending the constitution. To consolidate his authority and gain public support, Park focused on rapid economic growth and high export performance as a means to legitimize his regime. The decision to prioritize heavy industries was partly influenced by Japan's post-World War II experience, where Japan initially focused on light manufacturing before shifting its focus to heavy industries in 1957, achieving remarkable growth and export success by the late 1960s.

National security concerns also have been pointed out as a driver of the policy (e.g., Lane, forthcoming). Following the Nixon doctrine, the US announced a partial withdraw of its military troops from South Korea, raising concerns about national defense amid rising military tensions with North Korea. Developing the heavy manufacturing sectors was regarded as a necessary step to strengthen South Korea's military capabilities.

Focus on adoption of modern technology. While promoting the heavy manufacturing sectors, the central focus of the government was modernizing technology, as emphasized by its slogan "nation-building through science and technology, and technological self-reliance (과학입국 기술자립)." Given its large technology gap with the world frontier, the government deemed technology adoption to be one of the most effective ways to catch up with the frontier, make the country richer, and achieve technological self-reliance in the near future (Amsden, 1989).[1] Technology adoption was the primary channel of technology transfer from advanced economies to South Korea, as foreign direct investment—another commonly used means of technology transfer—was restricted by regulations imposed to limit the economic power of foreign multinational firms (Kim, 1997, p. 42-43).

Subsidy instrument. The government selectively provided subsidies to a subset of adoption contracts based on their potentials for large economic gains and spillovers. One of the main subsidy instruments was the allocation of foreign credit (Choi and Levchenko, 2024). Due to the balance of payment concerns, the government strictly regulated Korean firms from borrowing US dollars from foreign financial institutions, fearing dollar outflows. This was enforced through the Foreign Capital Inducement Act. The government allocated foreign credit selectively to domestic firms to facilitate adoption of advanced foreign technology and purchases of capital equipment needed to implement these technologies (Enos and Park, 1988). This directed credit functioned effectively as subsidies for adoption, because most transactions with foreign firms were denominated in dollars, and the government provided guarantees for the credit. As a result, firms could borrow at significantly lower interest rates than those available from other sources.

Temporary nature of the policy. The HCI Drive was a temporary policy that ended in 1979 following the assassination of President Park, a key element of the big push narrative. After Park's death, President Chun, who came to power through a military coup, shifted towards more market-oriented liberalization policies rooted in neoliberal principles, aiming to distance his administration from the politics of the Park era (Haggard and Moon, 1990).[2] In line with these principles, the new government discontinued subsidizing the heavy manufacturing sectors. Appendix Figure B2 shows that foreign credit allocated to the heavy manufacturing sectors surged only between 1973 and 1979, supporting the narrative of the policy's temporary nature.

Other policies. In addition to focusing on technology adoption, the government implemented a range of other policies to promote the heavy manufacturing sectors, such as the construction of industrial complexes (Kim et al., 2021; Choi and Levchenko, 2024), export promotion through international trade fairs (Barteska and Lee, 2023), and input tariff exemptions for exporters (Connolly and Yi, 2015). Unlike these studies, our analysis focuses on the technology adoption channel. However, these other policies raise concerns about endogeneity in our empirical setting, as firms that benefited from technology adoption may have also received other forms of government support. We later explain how our empirical strategies isolate these other channels.

[1] "It is necessary to encourage investment from private firms in technology and to maximize the government's investment in it. Efforts must also be directed toward increasing technology adoption . . . 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).

[2] Although the HCI Drive spurred growth in heavy manufacturing, it also intensified political tensions by increasing wealth concentration and widening rural-urban inequalities. In response, President Chun pursued market-oriented reforms to distance from the Park era, including abolishing government-guaranteed credit, privatizing banks, and bailing out unproductive chaebols.

2.2 Data

We construct our main dataset by merging firm-level balance sheet data with information on firms' technology adoption activities. Our dataset covers manufacturing firms between 1970 and 1982, classified into 10 broad manufacturing sectors. Among these 10 sectors, 4 sectors are categorized as heavy manufacturing. The data is aggregated to 86 regions. Further details regarding the data construction can be found in Appendix A.

Technology adoption. We manually collected and digitized firm-level data on technology adoption from official technology contract documents, sourced from the National Archives of Korea, and surveys published by the Korea Industrial Technology Association.[3] These documents contain information about names of domestic and foreign contract parties, and the calendar years in which the contracts were made, covering the period from 1962 to 1988. Between 1970 and 1982, during the periods with available balance sheet information, 1,634 contracts were signed by 587 unique Korean firms.[4] Of these contracts, 85% were in heavy manufacturing sectors, and 95% involved the transfer of know-how, such as blueprints or training services provided by foreign firms.[5]

Balance sheet, business group affiliation, and geographic information. Firm balance sheet data is obtained by digitizing the Annual Reports of Korean Companies published by the Korea Productivity Center. These reports cover firms with more than 50 employees, with information on sales, assets, fixed assets, and exports from 1970 to 1982 (with employment data available starting from 1972). All monetary values are converted into 2015 US dollars. It covers 6,230 unique firms, 47% classified as heavy manufacturing, and is representative at the national level, covering 70% of national manufacturing gross output. To the best of our knowledge, this is the first paper to use firm panel data from 1970s South Korea.[6] We merge the balance sheet data with the technology adoption data based on firm names.

Some observations reported missing information on employment. Due to this missing data and the fact that employment is only available from 1972 onward, the sample size decreases when using employment variables. To more leverage the data, we drop these observations only when employment is required in the analysis, and conduct robustness checks related to this missing data issue.

The annual survey also has information on addresses of firms' plants and affiliated business groups (also known as chaebols). Using this information, we link their adoption activities to their respective production locations. We use the business group affiliation information to construct the IV

[3] Once approved for technology adoption, firms had to report to the Economic Planning Board, which guided South Korea's economic policies. From 1961 to the mid-1980s, the board held monthly meetings on new technology contracts, with related documents preserved in the National Archives of Korea.

[4] Among these 1,634 contracts, 57% came from Japan and 21% from the US (Appendix Figure B5).

[5] For example, Appendix Figure A1 is a page from a contract between Korean and Japanese chemical manufacturers (Kolon and Mitsui Toatsu). The contract specified that Mitsui was required to provide blueprints, send skilled engineers to train Korean workers, and offer training services at their plants in Japan.

[6] Exceptions are Choi and Shim (2023), Choi and Levchenko (2024) and Choi et al. (2024), who also use the same dataset constructed for this study.

Table 1: Descriptive Statistics

Var.	Firm-year level							Firm level			
	Sales (mln 2015 USD) (1)	Emp (thousands) (2)	Fixed asset (mln 2015 USD) (3)	Dum. export (4)	Dum. adoption (5)	Dum. subsidy (6)	Dum. export promo. (7)	Ever export (8)	Ever adoption (9)	Ever subsidy (10)	Ever export promo. (11)
	Panel A. All firms										
Mean	30.89	0.55	13.93	0.30	0.03	0.01	0.03	0.39	0.09	0.03	0.08
SD	174.59	1.42	106.46	0.46	0.17	0.11	0.18				
N	29,786	17809	29633	29,786	29,786	29,786	29,786	6,230	6,230	6,230	6,230
	Panel B. Ever-adopters										
Mean	103.17	1.31	52.86	0.44	0.18	0.04	0.08	0.65	N/A	0.18	0.23
SD	377.98	2.54	245.67	0.5	0.39	0.2	0.27				
N	4,871	3,464	4,862	4,871	4,871	4,871	4,871	587	587	587	587
	Panel C. Never-adopters										
Mean	16.76	0.37	6.29	0.27	N/A	0.01	0.03	0.36	N/A	0.02	0.06
SD	85.4	0.88	36.87	0.44	N/A	0.07	0.16				
N	24,915	14,345	24,771	24,915	N/A	24,915	24,915	5,643	5,643	5,643	5,643
	Panel D. Business group firms										
Mean	142.06	1.95	68.34	0.51	0.13	0.07	0.12	0.75	0.46	0.26	0.30
SD	344.69	3.20	153.15	0.50	0.34	0.25	0.33				
N	2,601	1,940	2,600	2,601	2,601	2,601	2,601	306	306	306	306

Notes. Columns 1-7 of this table report the descriptive statistics of balance sheet variables and dummies of exporting, adopting foreign technologies, receiving directed credit (subsidy), and participating in international trade fairs (export promotion), respectively, at the firm-year level between 1970-1982. Columns 8-11 report the fraction of firms that ever exported, adopted foreign technologies, received directed credit, and participated in international trade fairs, respectively, among the set of unique firms that operated at any time between 1970-1982. Panels A, B, C, and D present data for all firms, ever-adopters, never-adopters, and firms affiliated with business groups, respectively. All monetary values are converted into 2015 US dollars.

for local spillovers and complementarity. There are 59 business groups, with an average of 5 firms per group. Appendix Table A2 reports business groups' distributions of firms across sectors.

Directed credit and export promotion. Unobserved government support is a significant source of endogeneity for our empirical analysis. Related to this concern, we acquire firm-level information on two types of government support: directed foreign credit allocated by the government and export promotion. We use this information to serve as control variables and to assess the validity of the identifying assumptions of our empirical analysis.

Credit data, a primary instrument for subsidizing technology adoption, comes from Choi and Levchenko (2024), who compiled information on total amounts of foreign credit allocated by the government. While we have annual information on total credit received by each firm, specific amounts allocated to each contract are not available. The government also promoted firm exports through Korea's Trade Promotion Agency (KOTRA), established in 1962, that provided firms with opportunities to attend international trade fairs and connect with foreign buyers. Using KOTRA's Annual Reports on International Trade Fairs, a source first used by Barteska and Lee (2023), we obtain information on each firm's total contract values and attendance at trade fairs.

Sectoral and regional data. We obtain import tariffs from Luedde-Neurath (1986), input-output tables from the Bank of Korea, and regional population from the Population and Housing Census.

Descriptive statistics. Columns 1-7 of Table 1 report descriptive statistics of the balance sheet variables and dummies for export, adoption, and receipt of government support (credit and export promotion) at the firm-year level. Columns 8-11 report shares of firms that ever exported, adopted technologies, and received government support. Out of the 6,230 firms, 9.4% (587 firms) adopted technologies at least once, classified as "ever-adopters." On average, these ever-adopters were larger (516% higher sales and 254% higher employment) and more likely to receive government support than "never-adopters" (Panels B and C), highlighting systematic differences between the two groups. About 5% (306 firms) were affiliated with business groups, which were also larger and more likely to adopt technologies and receive government support (Panel D).

3. Empirical Evidence on Firm-Level Effects of Technology Adoption

In this section, we present three empirical findings on the firm-level effects of technology adoption that support the big push hypothesis: direct effects on adopters, local spillovers to non-adopters, and local complementarity in firms' adoption decisions.

3.1 Direct Effects on Adopters

Winners vs. losers research design. One of the main econometric challenges in estimating the direct effects on adopters is the presence of unobservable differences between adopters and non-adopters. To address this, we implement a winners vs. losers research design, which compares adopters that successfully adopted technology (winners) with non-adopters who initially signed contracts but ultimately *failed* or were *delayed* in adopting due to external factors (losers).[7] Winners serve as the treated group, while losers serve as the control group. This design allows us to control for unobservables that may have influenced firms to self-select into adoption.

Losers are defined as firms that signed contracts, which were approved by the government, but failed or were delayed in adopting because the foreign party canceled the contract for reasons that were plausibly exogenous to the losers. Examples of such cancellations include foreign firms' bankruptcy, changes in management team, or sudden requests for modifications to contractual terms after initial agreements were made. We exclude cancellations initiated by Korean firms, such as those driven by sudden cash flow issues, to minimize concerns about endogeneity. When contracts were canceled after government approval, Korean firms had to report the reasons to the government. We manually gathered these cancellation cases from related documents.

There are two types of losers: delayed-adopters and never-adopters. Delayed-adopters are firms that eventually adopted technology but experienced a delay due to the cancellations. Never-adopters are firms that did not adopt technology at any point following the cancellations. As a result, the

[7] This empirical strategy makes a connection with Greenstone et al. (2010), who identify spillovers by comparing winning counties that attracted a large manufacturing plant opening and losing counties that were the new plant's runner-up choice.

cancellations create exogenous variation in the timing of adoption for some firms and in the adoption status for 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. The matching procedure involves two steps. First, we match exactly on region-sectors to absorb common shocks within region-sectors, such as market size or local labor market conditions. Second, within region-sectors, we select winners most similar to a loser based on the Mahalanobis distance, using four firm size variables: log assets, log fixed assets, and their one-year growth rates. This matching is with replacements, meaning that one winner can be matched with multiple losers. If more than three candidates for winners are available, the most similar three are selected; if fewer than three, all candidates are included. This matching results in 38 matches among 106 unique firms. Among these 38 matches, there are 25 not-yet-treated losers and 13 never-treated losers. For some matches with cancellations occurring in later periods, the main dataset—covering up to 1982—provides insufficient post-treatment observations. To address this, we supplement the dataset with KIS-VALUE, which provides balance sheet information for periods beyond 1982.[8]

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

$$y_{imt} = \sum_{\tau=-5}^{7} \beta_\tau \left(D_{mt}^{\tau} \times \mathbb{1}[\text{Winner}_{it}] \right) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{3.1}$$

where i denotes firm, m match, and t year. y_{imt} is firm outcomes. 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 of winner status. We normalize β_{-1} to zero. δ_{im} and δ_{mt} are match-firm and match-year fixed effects, respectively. ε_{imt} is the error term. We also consider a pooled diff-in-diff specification:

$$y_{imt} = \beta \left(\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}] \right) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{3.2}$$

where $\mathbb{1}[\text{Post}_{mt}]$ is a post-treatment dummy. In both specifications, standard errors are two-way clustered at the match and firm levels to account for potential correlation in residuals.[9]

We use two standard measures for performance outcomes, log sales and revenue TFP (TFPR) obtained as residuals from production functions estimated via the control function approach (Levinsohn and Petrin, 2003; Ackerberg et al., 2015).[10] We account for the possibility that adoption may affect underlying TFP processes by adapting the estimation procedure of De Loecker (2013). We lose some

[8] KIS-VALUE covers firms with assets over 3 billion Korean Won (2.65 million USD in 2015), capturing only a subset of larger firms from our main dataset, which also includes smaller firms below this threshold. However, this irregular coverage is not an issue, as most losers and winners are large firms above the threshold.

[9] Matching with replacement introduces mechanical correlation across residuals, as the same firm may appear in multiple matches. Clustering at the firm level addresses this issue.

[10] Our main balance sheet data do not have information on material inputs. Therefore, we estimate value-added production function using KIS-VALUE data over the period 1980-1995, which has material input information, and value-added calculated as sales times value-added shares from the input-output tables, following Ackerberg et al. (2015). Then, we obtain labor and capital elasticities and obtain TFPR as residuals for the sample between 1970-1982. We cannot apply Gandhi et al. (2020) due to the lack of data on intermediate inputs in the main dataset.

observations for TFPR due to missing employment data.

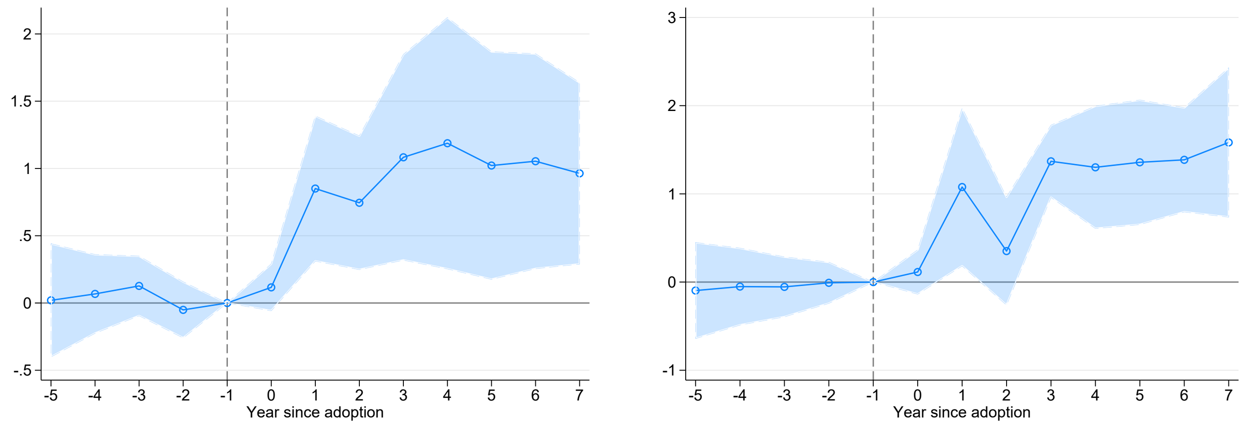
An additional issue is related to the staggered diff-in-diff design, which introduces bias in the presence of heterogeneous treatment effects across cohorts (e.g., Sun and Abraham, 2021; Borusyak et al., forthcoming). To address this issue, we adopt the stacked-by-event design (e.g., Cengiz et al., 2019) and construct the estimation dataset based on rolling control groups. We drop matches when delayed-losers adopt technology in later periods. This design ensures that the event study coefficients are identified based solely on within-match comparisons between treated winners and not-yet-treated or never-treated losers.

Identifying assumption. Our identifying assumption is that losers serve as valid counterfactuals for winners. We require that losers and winners were ex-ante similar in terms of both observables and unobservables before the event and that cancellations were uncorrelated with domestic firms' unobservables. Raw data plots support this assumption: the average log sales of winners began to increase only after successful adoption, while those of losers followed their pre-trends after the events (Appendix Figure B3). Also, despite the small number of losers, the distribution of cancellations across sectors closely mirrors that of the total contracts, supporting the notion that cancellations were random events (Appendix Figure B4).

To further test this assumption, we conduct three exercises. First, we assess covariate balance between winners and losers prior to the cancellations (Appendix Table B1). Both groups are well-balanced for the variables used for matching, as well as other variables, such as receipt of government support (credit and export promotion) and affiliation with large business groups. We also compare patenting activities between two groups of foreign firms that made contracts with winners and losers, using data from the US Patent and Trademark Office. The patenting activities between the two groups are balanced, ruling out the possibility that losers were matched with less competent foreign firms. Moreover, if cancellations were random, losers' characteristics should be balanced with not only matched adopters but also with all adopters in the same region-sector-year, which is also confirmed by the data. Second, we perform a balance test by regressing pre-event observables on dummies indicating loser status (Appendix Table B2). None of these observables predict cancellations. Third, and most importantly, we inspect pretrends.

Another concern is the potential violation of the Stable Unit Treatment Values Assumption (SUTVA) due to local spillovers from winners to losers or increased local competition. Positive spillovers from winners to losers would lead to underestimation of the true impacts of the direct effects, making our estimates conservative lower bounds. Also, any spillovers from other local firms, common at the region-sector level, are absorbed out by match-year fixed effects, as matches are within the same region-sector. In the case of increased local competition, we would expect to see observable negative changes in the trends of losers after the events. However, no such changes are detected in the raw plot of sales. Furthermore, because manufacturing sectors are highly tradable and the spatial unit of analysis is quite granular, competition effects are unlikely to significantly influence the results.

Figure 2: Direct Effects on Adopters: Winners vs. Losers Design



A. Log sales

B. Revenue TFP

Notes. Panels A and B present the estimated β_τ for log sales and revenue TFP, respectively, in equation (3.1) based on the winners vs. losers research design. The dotted lines represent the 95% confidence intervals based on standard errors two-way clustered at the match and firm levels. All specifications include match-year and match-firm fixed effects.

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

$$y_{it} = \sum_{\tau=-5}^{7} \beta_\tau (D_{it}^{\tau} \times \mathbb{1}[\text{Adopt}_{it}]) + \delta_i + \delta_{njt} + \varepsilon_{it}. \tag{3.3}$$

$\mathbb{1}[\text{Adopt}_{it}]$ is a first-time adoption dummy. δ_{njt} are time-varying region-sector fixed effects that absorb out any common shocks at the region-sector-year level, similar to match-year fixed effects in the winners vs. losers research design. Standard errors are clustered at the region level.

Baseline results. Figure 2 and Table 2 report the estimated coefficients of equation (3.1). There are no pretrends. Both winners' sales and TFPR start to increase only after the adoption. Four years post-adoption, sales and TFPR rise by 119% and 130%, respectively, with these effects remaining persistent. The pooled diff-in-diff estimators indicate that sales and TFPR increase by 91% and 94%, respectively, during post-adoption periods.[11]

The TWFE estimators also indicate increases in adopters' sales post-adoption, but there are noticeable pretrends at $t = -4$, and the magnitude is about 75% smaller than the baseline. TFPR shows comparable patterns. These discrepancies may reflect the government's preferential treatment of politically connected firms with low productivity. Kim et al. (2021) provide supporting evidence, showing

[11] The magnitude of these estimates aligns with the findings of Giorcelli and Li (2023), who examine the impact of Soviet technology transfers on Chinese steel plants and report a 25% increase in TFPQ six years after the transfers. Under monopolistic competition, where TFPQ $\propto \frac{\ln \text{Sale}}{\sigma - 1}$, and with commonly calibrated σ values ranging from 3 to 4, our sales estimate at $t = 6$ implies a TFPQ increase of 35% to 52%.

Table 2: Direct Effects on Adopters

Research design	Winners vs. losers				Full sample TWFE			
Dep. var.	Sale	TFPR	Subsidy	Export promo.	Sale	TFPR	Subsidy	Export promo.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Event study							
5 years before	0.02	−0.10	0.02	−0.07	−0.19**	−0.04	−0.00	−0.02
	(0.21)	(0.28)	(0.09)	(0.08)	(0.07)	(0.08)	(0.01)	(0.01)
4 years before	0.07	−0.05	0.09	−0.02	−0.09	−0.05	0.01	0.01
	(0.15)	(0.22)	(0.09)	(0.10)	(0.07)	(0.07)	(0.01)	(0.02)
3 years before	0.13	−0.05	0.01	−0.00	−0.04	−0.01	−0.00	0.00
	(0.11)	(0.17)	(0.08)	(0.11)	(0.06)	(0.06)	(0.01)	(0.01)
2 years before	−0.05	−0.01	0.05	0.05	−0.00	0.01	0.01	0.01
	(0.11)	(0.12)	(0.07)	(0.04)	(0.05)	(0.05)	(0.01)	(0.02)
1 year before								
Year of event	0.12	0.11	0.03	0.01	0.08*	−0.01	0.02***	0.02
	(0.09)	(0.13)	(0.08)	(0.09)	(0.05)	(0.04)	(0.01)	(0.01)
1 year after	0.85***	1.08**	0.01	−0.05	0.19***	0.08	0.04**	0.02
	(0.28)	(0.46)	(0.09)	(0.11)	(0.06)	(0.05)	(0.02)	(0.02)
2 years after	0.74***	0.35	0.04	0.02	0.13	0.09	0.02**	0.06***
	(0.25)	(0.31)	(0.12)	(0.12)	(0.10)	(0.10)	(0.01)	(0.02)
3 years after	1.08***	1.37***	0.09	−0.15	0.20**	0.11	0.01	0.03
	(0.39)	(0.21)	(0.11)	(0.11)	(0.10)	(0.12)	(0.01)	(0.02)
4 years after	1.19**	1.30***	0.04	0.02	0.24**	0.17	0.01	0.02
	(0.48)	(0.35)	(0.11)	(0.13)	(0.12)	(0.15)	(0.02)	(0.03)
5 years after	1.02**	1.36***	−0.03	−0.08	0.30***	0.24**	−0.02	0.05
	(0.43)	(0.36)	(0.09)	(0.15)	(0.10)	(0.09)	(0.02)	(0.03)
6 years after	1.05**	1.39***	−0.03	−0.08	0.32***	0.23**	0.02	0.05
	(0.41)	(0.30)	(0.09)	(0.15)	(0.11)	(0.11)	(0.02)	(0.03)
7 years after	0.96***	1.58***	−0.03	−0.08	0.32***	0.20*	−0.01	0.04
	(0.34)	(0.43)	(0.09)	(0.15)	(0.09)	(0.11)	(0.02)	(0.03)
	Panel B. Pooled diff-in-diff							
Adoption × Post	0.91***	0.94***	−0.01	−0.05	0.17**	0.10	0.01**	0.03**
	(0.30)	(0.34)	(0.06)	(0.10)	(0.07)	(0.07)	(0.01)	(0.01)
# Clusters	38 × 106	35 × 98	38 × 106	38 × 106	82	63	82	82
N	852	537	852	852	21319	11,994	21,319	21,319
Fixed effects	Match×Firm, Match×Year				Firm, Region×Sector×Year			

Notes. Standard errors in parentheses are two-way clustered at the firm and match levels in columns 1-3, and at the region level in columns 4-6. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Panel A of 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 (3.3)), respectively. Panel B reports the estimates from the corresponding pooled diff-in-diff specifications (equation (3.2)). The dependent variables are log sales, revenue TFP (TFPR), dummies indicating the receipt of directed credit (subsidy), and dummies of participating in international trade fairs (export promotion). In columns 2 and 6, the sample size decreases due to missing employment data. The coefficient β_{-1} is normalized to zero. Columns 1-3 include match-firm and match-year fixed effects, while columns 4-6 include firm and region-sector-year fixed effects.

that allocative efficiency worsened during the HCI Drive and arguing that such preferential treatment may have contributed to this decline.

Results unlikely to be driven by subsidy and export promotion. Even if the identifying assumptions hold, a potential concern arises regarding the interpretation of these estimates: they may capture government support rather than the *pure* effects of technology adoption. For example, if the government reclaimed subsidies from losers or reduced export promotion activities for losers following cancellations, the estimates might reflect the *joint* effects of both adoption and government support.

To investigate this concern, we include dummies for receiving government support (credit and export promotion) as outcomes. In the TWFE specification, coefficients for these variables become positive and statistically significant at the 1% level after adoption (col. 7-8). However, in the winners vs. losers specifications, we do not observe such increases following adoption (col. 3-4; see also Appendix Figure B3). These findings suggest that our main results for sales and revenue TFP reflect the *pure* effects, rather than the *joint* effects with government support. For unobserved government support to undermine our interpretation, it would need to be uncorrelated with both observed directed credit and export promotion—an unlikely scenario, as subsidies are likely correlated with each other.

Further discussions on the interpretation. The results show that technology adoption expanded the size of adopters during the rapid industrialization. However, from sales and revenue TFP alone, we cannot fully disentangle the channels driving this expansion. For instance, increased sales may reflect either physical productivity gains or demand shocks due to selling more tailored inputs to foreign technology sellers. We can, however, rule out certain alternative explanations. First, the findings are not driven by demand shocks related to government military spending, as none of the matched firms had military contracts with the government.[12] Second, the raw sales plot in Appendix Figure B3 shows no negative trend changes for losers following cancellations, ruling out the possibility that cancellations adversely affected them.[13]

Alternative inferences and estimators. To address potential finite sample bias due to highly leveraged observations, we conduct randomization inference (Young, 2019). Regarding small numbers of clusters, we report wild bootstrap p-values (Cameron et al., 2008; MacKinnon et al., 2023). We also consider alternative clustering at the match or firm levels. These inference procedures yield p-values nearly identical to the baseline estimates (Appendix Table B4). Alternative staggered diff-in-diff estimators, developed by Sun and Abraham (2021) and Borusyak et al. (forthcoming), provide estimates within the 95% confidence intervals of our baseline event-study estimates (Appendix Figure B6).[14] Moreover, using the methodology proposed by Rambachan and Roth (2023), we show that the results remain robust to mild violations of the parallel trends assumption (Appendix Figure B7).

Alternative outcomes and estimation samples. We consider alternative outcomes including labor productivity (sales per employee), revenue TFP based on Olley and Pakes (1996), log fixed asset, and a dummy for exporting. Adoption has positive impacts on these outcomes. We consider a subsample without missing employment data and different matching procedures—varying the number of winners matched to each loser or including all firms that adopted technologies in the event year within

[12] Due to the Act on Special Measures for Defense Industry, all government military contracts have been awarded to pre-registered firms. We have access to the list of these firms and can check whether winners or losers were in the list.

[13] For example, losers might have anticipated contract execution and purchased new equipment designed for the modern technologies they planned to adopt. If the adoption failed, they might have been left with equipment inappropriate for the traditional technologies they were already using.

[14] For the Sun and Abraham (2021) estimators, we use the never-treated losers as a control group. Also, the pretrend tests developed by Borusyak et al. (forthcoming) show no statistically significant pretrends for all four dependent variables.

the corresponding losers' region-sectors. The results remain robust (Appendix Table B5).

3.2 Local Spillovers

Next, we examine local spillovers from technology adoption. We define region-sector nj's adopter shares in in year $t-h$ as

$$\text{Share}_{(-i)nj,t-h} = \frac{T_{(-i)nj,t-h}}{N_{(-i)nj,t-h}}. \tag{3.4}$$

$N_{(-i)nj,t-h}$ is the total number of firms in nj in $t-h$, excluding firm i to rule out the mechanical correlation. $T_{(-i)nj,t-h}$ is the number of firms in nj that ever adopted foreign technology in $t-h$, also excluding i. Lagging by h years allows for the possibility that it took time for local diffusion of new knowledge from adopted technologies. We set the baseline value of h to 2.

Because the IV, which will be detailed below, predicts changes in local-level adopter shares rather than their levels, we consider the following long-difference specification:

$$\Delta y_{it} = \beta \Delta \text{Share}_{(-i)nj,t-2} + \zeta y_{it_0} + \mathbf{X}'_{injt}\gamma + \delta_n + \delta_j + \sum_g D_g \delta_{jg} + \Delta\varepsilon_{it}, \tag{3.5}$$

where g denotes business groups. The dependent variables are changes in log sales or TFPR. The time-invariant factors are differenced out. δ_n and δ_j are region and sector fixed effects. For firms affiliated with group g ($D_g = 1$), where D_g is a dummy for group affiliation, we include group-sector fixed effects δ_{jg}, which absorb group-sector level common factors, such as within group-sector spillovers. We include the initial dependent variables y_{it_0} to account for the well-documented fact that larger firms grow slower, but as a robustness check, we also consider omitting y_{it_0}. $\mathbf{X}_{injt}$ is a vector of additional controls. Standard errors are two-way clustered at the region and business group levels, with individual firms not affiliated with any groups subject to their own group-level clusters.[15]

The coverage is incomplete in the early years, and not all firms appear in every year. To make more efficient use of the data and increase firm coverage, we employ overlapping long differences for 1972-1979 and 1973-1980. These time spans cover the policy period. Because standard errors are clustered at the regional level, this approach is innocuous. Dummies for each set of differences are included in the specifications.

Adopter shares can influence firm performance through both spillovers and their influences on firms' adoption decisions. To focus exclusively on the spillover channel, the estimation sample includes only firms that never adopted technology. The estimates based on the never-adopter sample reflect only the spillovers, as these firms did not benefit directly from adoption. To account for potential sorting, we estimate equation (3.5) only for continuing firms, but firm entry and exit affect variation

[15] Kelly (2019) shows that previous studies sensitive to spatial correlation tend to have high z-scores in the Moran test. In our data, the Moran test indicates that spatial autocorrelation becomes insignificant beyond 75 km (Appendix Table B12). The median (mean) size of our regions is 597 km^2 (638 km^2), suggesting that the level of clustering in our analysis exceeds the potential spatial correlation present in the data. Additionally, we show that our results remain robust when applying the spatial HAC estimators (Conley, 1999; Colella et al., 2021).

in adopter shares, our main variable of interest.

IV strategy. The OLS estimates may be biased by endogeneity, as region-sector unobservables could affect both local firms' adoption decisions and their growth. The direction of the OLS bias is ex-ante ambiguous. On the one hand, positive regional productivity shocks could lead to upward bias. On the other hand, unobserved subsidies provided to less productive but politically connected firms may introduce downward bias. Additionally, measurement errors in adopter shares, caused by incomplete data coverage, present another source of downward bias. Restricting the sample to never-adopters may also lead to selection bias.

To address these issues, we construct an IV based on the spatial network of business groups that own multiple firms across region-sectors. We define:

$$Z^{\geq 100\text{km},t_0}_{inj,t-h} = \sum_{\tilde{g} \neq g(i)} D_{\tilde{g}njt_0} \times \frac{T^{\geq 100\text{km},t_0}_{\tilde{g}(-n)j,t-h}}{\tilde{N}^{\text{P}}_{(-i)nj,t-h}}.$$

$T^{\geq 100\text{km},t_0}_{\tilde{g}(-n)j,t-h}$ is the total number of sector j adopters in year $t-h$ that operated and were affiliated with business group $\tilde{g}$ in the initial year t_0, excluding firms located in region n or within a 100 km radius of region n. $D_{\tilde{g}njt_0}$ is a dummy variable indicating whether business group $\tilde{g}$ had at least one firm in region-sector nj in the initial year t_0. We sum $T^{\geq 100\text{km},t_0}_{\tilde{g}(-n)j,t-h}$ over business groups that had at least one firm in nj in the initial year (i.e., $D_{\tilde{g}njt_0} = 1$) and normalize the summation by $\tilde{N}^{\text{P}}_{(-i)nj,t-h}$, the predicted number of firms in nj in $t-h$, excluding i. This predicted number is constructed using national-level growth and the initial number of firms: $\tilde{N}^{\text{P}}_{(-i)nj,t-h} \equiv g_{(-n)j} \times N_{(-i)nj,t_0-h}$, 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 in year $t_0 - h$, excluding i.

The IV is constructed as the long-difference of $Z^{\geq 100\text{km},t_0}_{inj,t-h}$:

$$\text{IV}^{\geq 100\text{km},t_0}_{inj,t-h} = \Delta Z^{\geq 100\text{km},t_0}_{inj,t-h}. \tag{3.6}$$

The superscripts t_0 and ≥100km emphasize that the IV is constructed using only *pre-existing* firms that were already operating before t_0 and located outside a 100 km radius of focal regions.

The IV strategy leverages the idea that group-level technology adoption decisions can serve as exogenous shifters for adopter shares in focal regions where the group initially owned firms.[16] To further illustrate the idea behind the IV, let's consider the Samsung group as an example. The group owned six firms in the electronics sector, with four located in Suwon (northwest region) and two in Ulsan (southeast region), distanced by 283 km (176 miles). Suppose Samsung made a group-level decision to adopt modern technologies, driven by either higher group-level productivity or subsidy

[16]This IV approach is also related to recent studies that use spatial networks of firms to construct local-level exogenous variation. For example, Moretti (2021) uses spatial network of multi-region firms to construct an IV for local inventor cluster size. Giroud et al. (2024) study the role of plant-level networks of multi-region firms in propagation of local productivity spillovers through their shared knowledge.

shocks. This decision would increase the overall adoption levels across its affiliated firms. These group-level factors are extracted by four firms's adoption in Suwon, but because they are outside of Ulsan, these factors are unlikely to be correlated with Ulsan's local shocks. Thus, they act as exogenous shifters for adopter shares in Ulsan for firms not affiliated with Samsung.

The identifying assumption is that firm-level outcomes in certain region-sectors—where the initial firm composition was more concentrated with business groups that later heavily adopted technologies—would have otherwise evolved similarly to those in other region-sectors. More explicitly, we assume that for firm i, variation in the number of adopters, outside of i's region, which had operated before the initial year and were initially affiliated with business groups owning a firm located in i's region, was orthogonal to i's unobservables, conditional on covariates.

Threats to identification. We discuss three potential threats to identification. First, the expansion of large business groups may affect region-sector variables, though region fixed effects control for changes in region-wide factors like wages and amenities, potentially violating the exclusion restriction. For example, business groups may not only adopt technologies but also invest in infrastructure, such as energy or transportation, during expansion, benefiting local firms beyond the spillovers from adoption. To address this, we include business groups' sales shares within region-sectors in the regressions. Because this variable may be endogenous, we construct an IV for it, similar to the one for adopter shares, and include this IV directly in a reduced-form fashion (see Appendix B.2 for details on the construction of these variables). This variable helps isolate *variation in the predicted adopter shares* from *variation in business group size* within region-sectors, allowing us to capture the local effects of technology adoption separately from the effects associated solely with the size of business groups. For instance, some business groups may expand their size without adopting technologies, while others might simultaneously grow in size and upgrade their technologies. The business groups' sales shares capture local effects stemming from pure size expansion in both types of groups. In contrast, adopter shares capture spillovers specifically tied to adoption by the latter type.

Second, business groups' sorting can be an issue. There can be two potential types of sorting. The first type is that business groups may have sorted into specific region-sectors during their expansion between 1972-1980. However, because our IV relies only on *pre-existing firms*, this type of sorting is not a concern. The second type involves the possibility that persistent unobservable shocks prior to 1972 or 1973 affected the initial location choices of business groups. To address this concern, we perform a placebo test by examining whether the IV predicts firm performance before 1972 or 1973. If such persistent shocks were present, the IV would correlate with past performance. However, we find no significant correlations, ruling out this possibility (Appendix Table B11).

Third, the SUTVA might be violated due to spatial interactions with neighboring business group firms through input-output linkages, such as supplying cheaper inputs or being major buyers. Excluding firms within a 100 km radius in the IV mitigates this concern, as the gravity literature shows

Table 3: Local Spillover

	OLS	IV						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Dep. $\Delta \ln \text{Sale}_{it}$ 1972-1979 or 1973-1980							
$\Delta\text{Share}_{(-i)nj,t-2}$	0.37	3.19***	2.70***	2.45***	2.62***	2.65***	3.00***	2.77***
	(0.42)	(0.74)	(0.74)	(0.77)	(0.74)	(0.73)	(0.78)	(0.84)
KP-F		17.83	21.54	17.87	21.48	20.25	22.00	16.12
# Clusters	$79 \times 1{,}294$							
N	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492
	Panel B. Dep. ΔTFPR_{it} 1972-1979 or 1973-1980							
$\Delta\text{Share}_{(-i)nj,t-2}$	−0.34	1.93***	1.60***	1.52***	1.55***	1.61***	1.68***	1.61***
	(0.38)	(0.62)	(0.55)	(0.55)	(0.57)	(0.54)	(0.54)	(0.54)
KP-F		18.54	22.86	19.87	22.22	22.69	27.35	19.42
# Clusters	67×742							
N	824	824	824	824	824	824	824	824
Fixed effects	Region, Sector, Sector×Group							
Business group sales share			✓	✓	✓	✓	✓	✓
Region-sector ctrl				✓				✓
Directed credit					✓			✓
Complex ctrl						✓		✓
Trade ctrl							✓	✓

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 (3.5). Adopter shares and IV are defined in equations (3.4) and (3.6), respectively. The sample consists of firms that never adopted technology during the sample period. In Panels A and B, the dependent variables are changes in log sales or TFPR between 1972 and 1979 or 1973 and 1980, respectively. In Panel B, the sample size decreases due to missing employment information. Columns 3-8 include business groups' predicted sales shares (equation (B.2), detailed in Appendix B.2). Column 4 includes controls for predicted market access (equation (3.7)) and log distance to port interacted with predicted exports. Column 5 includes the inverse hyperbolic sine transformation of cumulative credit received between 1972-1979 or 1973-1980. Column 6 includes industrial complex dummies and tax favors provided for firms located in industrial complexes. Column 7 includes changes in log import and input tariffs, interacted with log distance to port and initial export status, along with cumulative total contract values from international trade fairs between 1972-1979 or 1973-1980. Column 8 includes all additional controls. All specifications include region, sector, and sector-group fixed effects, and the initial levels of the dependent variables. KP-F is the Kleibergen-Paap F-statistics.

that internal trade flows sharply fall with distance.[17] We also include controls for market access.

Baseline results. Table 3 presents the estimation results. The dependent variables are changes in log sales in Panel A and revenue TFP in Panels B. In Panel B, sample size is reduced due to missing employment data. Columns 1 and 2 report the OLS and IV estimates, respectively. The IV is strong, with a first-stage coefficient of 0.19 and the Kleibergen-Paap F-statistics (KP-F) around 18, surpassing both the rule of thumb value of 10 and the threshold of 15.1 derived by Montiel Olea and Pflueger

[17]For example, Hillberry and Hummels (2008) find that shipment values within a 4-miles radius of a shipper are three times larger than those outside this radius.

(2013).[18] Appendix Table B6 provides the first-stage results.

Column 3 presents our preferred specification, which includes the predicted business groups' sales shares.[19] Including these predicted sales shares reduces the coefficient somewhat, as this variable isolates the variation in adopter shares from the variation in size of business groups, but improves first-stage strength. This estimate implies that a 1 percentage point increase in adopter shares leads to 2.7% higher sales and 1.6% higher revenue TFP.

The IV estimates are larger than the OLS estimates, which could be attributable to two factors. First, unobserved subsidies directed toward firms with lower productivity growth may lead to this downward bias, consistent with the divergence between the baseline and the standard TWFE estimates for the direct effects. Second, measurement errors could cause OLS to be downward biased.[20]

Additional controls. Our main findings remain robust after including additional controls. Following Donaldson and Hornbeck (2016), we construct market access variable, defined as:

$$\Delta \ln \mathrm{MA}^{\mathrm{p}}_{(-i)njt} = \Delta \ln \Big(\sum_{m,k} \sum_{i' \in \mathcal{F}_{(-i)mkt_0}} \mathrm{Dist}^{-\chi}_{nm} \times \gamma^{j}_{k} \mathrm{Sale}^{\mathrm{p}}_{i't} \Big). \tag{3.7}$$

where $\mathcal{F}_{(-i)mkt_0}$ is a set of firms in region-sector mk, excluding i, operating in the initial year t_0, and γ^j_k are the 1970 input-output coefficients. Internal trade costs are proxied using the distance between regions (Dist_{nm}), and χ is set to 1.5 (Costinot and Rodríguez-Clare, 2014). Due to endogeneity concerns, we use predicted sales instead of actual values computed as national-growth multiplied to initial sales: $\mathrm{Sale}^{\mathrm{p}}_{it} = g^{\mathrm{sale}}_{(-n)j} \times \mathrm{Sale}_{it_0}$, where $g^{\mathrm{sale}}_{(-n)j}$ is national-level sector j's growth excluding region n

To capture different regional exposure to export demand due to internal trade costs, we include log distance to the nearest port interacted with changes in the log sectoral exports. Similarly, we use predicted values for sectoral exports, computed as growth of imports (excluding imports from Korea) of the US and Japan—the two largest export markets for Korea—multiplied to initial sectoral exports. Appendix Figure B8 shows that these two variables are highly correlated with those based on actual values. Column 4 adds these two variables, confirming that our findings are robust.[21]

Column 5 includes the inverse hyperbolic sine transformation of the sum of directed credit received between 1972-1979 or 1973-1980. During the policy period, industrial complexes were built in southeastern regions (Kim et al., 2021; Choi and Levchenko, 2024). Using data from the 1980

[18] Montiel Olea and Pflueger (2013) propose a conservative test accommodating heteroskedasticity, serial correlation, and clustering. In the current setup with a single instrument, the KP-F is equivalent to their effective F-statistics. The value of 15.1 corresponds to the case of 20% relative bias at a 5% significance level.

[19] In Appendix Table B7, we also consider an alternative specification with two endogenous variables, where both adopter shares and business groups' sales shares are instrumented by their corresponding predicted values. This specification gives larger IV estimates for adopter shares. However, we prefer the specification with a single IV, as using two IVs may exacerbate the finite-sample bias of the IV estimates.

[20] When using yearly data with a fixed-effects model, the estimated coefficient is around 0.8, significant at the 5% level. The larger magnitude from the fixed-effects model is consistent with the presence of measurement errors, as first-difference models tend to magnify measurement errors relative to fixed-effects models.

[21] The results also hold with alternative market access measures, including those based on actual sales and those excluding firms from the same region-sector.

Yearbooks of Industrial Complexes, we add dummies for firms in these complexes and control for favorable tax treatment by calculating the years under tax exemptions, interacted with log sectoral effective marginal corporate tax rates. Column 6 reports the results.

Trade policies may impact regions differently due to internal trade costs, even though sector fixed effects absorb their common effects. To capture this, we include the log distance to port interacted with changes in both log import and input tariffs, with input tariffs computed using the 1970 input-output coefficients and import tariffs (Goldberg et al., 2010). We also include changes in the inverse hyperbolic sine transformation of each firm's total contract values from trade fairs to capture firm-level export promotion effects (Barteska and Lee, 2023). Finally, we control for firm-specific tariff exemptions on imported inputs for exporters (Connolly and Yi, 2015), by including dummies for initial export status interacted with input tariffs. Column 7 include these five trade-related variables.

Column 8 includes all additional variables jointly. The coefficient remains stable.

Further validation of the exclusion restriction. To further address concerns that groups might affect local factors, we re-run the regressions using alternative IVs that exclude business group firms whose fixed assets exceed 30%, 50%, and 70% of the total fixed assets within regions, because larger groups are more likely to influence regional variables.[22] We also consider excluding the two largest groups (Samsung and Hyundai). The results remain robust (col. 1-4 of Appendix Table B9). Regarding spatial interactions, we explore alternative radii, ranging from 50 km to 150 km, for the IV (col. 5-8 of Appendix Table B9). The lack of spatial correlations in residuals beyond 75 km based on Moran's I statistics further alleviates this concern (Appendix Table B12). We also check for correlations between the IV and observable credit or export promotion. In cases where the exclusion restriction is violated due to unobserved subsidies, we would expect the IV to be correlated with these variables. However, we find no such correlations (Appendix Table B10).

Alternative inference, spatial correlation, and weak IV. We use bootstrapped standard errors to address that outliers may exaggerate the statistical significance of the IV estimates (Young, 2022); spatial HAC standard errors to account for spatial auto-correlation (Conley, 1999); and the weak-IV-robust Anderson-Rubin test (Andrews et al., 2019) along with two-step confidence intervals developed by Andrews (2018).[23] The results remain robust (Appendix Table B14).

Firm entry and exit, alternative outcomes, lags, and samples, and omitting y_{it_0}. We examine entry and exit dummies as outcomes and find no significant effects, suggesting that these margins are unlikely to impact the results (Appendix Table B13). We consider alternative outcomes, including labor productivity, revenue TFP based on Olley and Pakes (1996), export dummies, and log fixed assets; omitting y_{it_0}; and using a 3-year lag. We push the IV's leave-out logic further by using a subsample of

[22] We use fixed assets because they better reflect local size of firms, as fixed assets (factories, capital equipment) are immobile, whereas sales reflect values of output sold outside of the region.

[23] While researchers often assess IV strength and report either conventional or weak-IV-robust confidence intervals accordingly, Andrews (2018) shows that this approach can introduce size distortions, which two-step confidence intervals can address.

firms unaffiliated with any business groups and operating in a single region. We consider excluding firms in industrial complexes and those with non-missing employment. The results remain robust (Appendix Table B15).

3.3 Local Complementarity in Adoption Decisions

Local levels of adoption could influence firms' decisions to adopt modern technologies. To investigate this relationship, we estimate equation (3.5) using the full sample including all firms (both never-adopters and ever-adopters), where we regress dummies indicating whether firms made new adoption contracts in given years ($\mathbb{1}[\text{New Contract}_{it}]$) on local adopter shares.[24] A positive coefficient for adopter shares suggests local complementarity, indicating that firms are more likely to adopt when other local firms have already adopted.

Columns 1 and 2 of Table 4 report the OLS and IV estimates, respectively. Once endogeneity is corrected for, the estimate becomes positive and statistically significant, the same pattern observed for the spillovers. The IV estimate in column 3, with the business groups' sales share control, suggests that a 1 percentage point increase in adopter shares leads to a 0.85 percentage point higher probability of making new contracts. This 0.85 percentage point increase represents approximately 14% of the average probability of making new contracts in 1979 and 1980, which was 6%. The IV is strong, with a *KP*-F of 17.7. Columns 4-8 include the same set of additional controls used in the spillover regression. The estimated coefficients remain positive, statistically significant, and stable.

Stronger complementarity with larger market access. Studies in international trade literature empirically document that larger market access boosts firms' productivity-enhancing activities (e.g., Verhoogen, 2008; Lileeva and Trefler, 2010; Bustos, 2011). Building on this, we examine how local complementarity varies with market access by interacting adopter shares with dummies indicating whether a region's initial market access—the control variable in column 4 (equation (3.7))—is above the 80th percentile. The estimated coefficient for regions above the 80th percentile is 1.07, compared to 0.29 for regions below this threshold, with the difference significant at the 10% level. The results hold across alternative percentile cutoffs (Appendix Table B8). These results highlight the role of market access in shaping the complementarity force, which we later connect to its role in enabling the big push in our quantitative analysis.

Robustness. Because the specifications for local complementarity mirror those for local spillovers and rely on the same variation, we conduct the same set of robustness exercises.[25]

[24] Note that $\mathbb{1}[\text{New Contract}_{it}]$ differs from the ever-adoption status used to construct adopter shares in equation (3.5). For example, if a firm had not adopted any foreign technologies previously but made its 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 would remain 1.

[25] See Appendix Table B6 for the first stage results; Table B7 for the specification with two endogenous variables; Table B9 for alternative IV construction; Table B11 for placebo; Table B14 for alternative inferences; Table B16 for robustness checks with alternative lags, estimation samples, and the omission of the initial dependent variable.

Table 4: Local Complementarity

Dep.	$\Delta\mathbb{1}$[New Contract$_{it}$] 1972-1979 or 1973-1980								
	OLS	IV							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\text{Share}_{(-i)nj,t-2}$	-0.08	0.79**	0.85**	0.82*	0.85**	0.90**	0.84**	0.87**	
	(0.11)	(0.36)	(0.41)	(0.43)	(0.42)	(0.41)	(0.40)	(0.39)	
Low MA $\times$ $\Delta\text{Share}_{(-i)nj,t-2}$									0.29*
									(0.17)
High MA $\times$ $\Delta\text{Share}_{(-i)nj,t-2}$									1.07*
									(0.56)
KP-F {min. SW-F}		13.91	17.71	17.47	17.81	17.15	19.05	18.09	21.11 {48}
# clusters	86 × 1,548								
N	1,977	1,977	1,977	1,977	1,977	1,977	1,977	1,977	1,977
Fixed effects	Region, Sector, Sector×Group								
Business group sales share			✓	✓	✓	✓	✓	✓	✓
Region-sector ctrl				✓				✓	✓
Directed credit					✓			✓	✓
Complex ctrl						✓		✓	✓
Trade ctrl							✓	✓	✓

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 (3.5). Adopter shares and IV are defined in equations (3.4) and (3.6), respectively. The dependent variables are changes in dummies of making new adoption contracts between 1972-1979 or 1973-1980. Column 9 includes interaction terms between adopter shares and dummies indicating low and high initial market access, defined based on the 80th percentile, along with the dummies for the 80th percentile thresholds. Columns 3-9 include business groups' predicted sales shares (equation (B.2), detailed in Appendix B.2). Column 4 includes controls for predicted market access (equation (3.7)) and log distance to port interacted with log predicted sectoral exports. Column 5 includes the inverse hyperbolic sine transformation of cumulative credit received between 1972-1979 or 1973-1980. Column 6 includes industrial complex dummies and tax favors provided for firms located in industrial complexes. Column 7 includes changes in log import and input tariffs, interacted with log distance to port and initial export status, and cumulative total contract values from international trade fairs between 1972-1979 or 1973-1980. Columns 8 and 9 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. min. SW-F is the minimum of Sanderson-Windmeijer F-statistics.

3.4 Summary and Discussion

To summarize, although adoption of modern technologies sizably increased both sales and TFPR for adopters, evidence on local complementarity shows that firms were less likely to adopt unless other local firms had already done so, suggesting coordination failures at the local level.[26] Local spillovers point to potential positive externalities, suggesting that private returns alone may not have been sufficient to overcome coordination failures. If the one-time big push resolved these failures, firms likely continued adopting even after subsidies ended, driving South Korea's industrialization.

[26]The case of POSCO—the first integrated steel mill in South Korea and now one of the top five steel producers globally—supports these findings, as detailed in Appendix B.1. 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 cheaper domestic capital inputs align with the three findings (POSCO, 2018, p.138-141).

4. A Simple Model of the Big Push

We present a simple dynamic model of the big push, which provides structural interpretations of the three empirical findings from the previous section.

Environment. We consider a closed economy with one sector and one region. Time is discrete, indexed by $t \in \{1, 2, \ldots\}$. Total labor endowment, a proxy for market size, is exogenously given as L. 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 a CES aggregator to produces final consumption goods. Representative households inelastically supply labor, which is the only factor of production.

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, $Q_t = (\int q_{it}^{\frac{\sigma-1}{\sigma}} \mathrm{d}i)^{\frac{\sigma}{\sigma-1}}$ 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. Their decisions to adopt modern technology, along with spillovers from technology adoption, endogenously determine their productivity in equilibrium. Firm productivity is composed of three components:

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

The first term $\eta^{T_{it}}$ governs direct productivity gains from adoption, where $\eta > 1$ and T_{it} is a binary variable equal to one if a firm adopts technology. The second term $f(\lambda_{t-1}^{T})$, common across firms, represents adoption spillovers that increase with the previous period's adopter share λ_{t-1}^{T}. Appendix C.4 provides two microfoundations for spillovers, which occur through labor mobility and knowledge transfers.[27] The third term ϕ_{it} is exogenous productivity, iid across firms and periods.

We assume the following functional form for spillovers:

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

where δ governs the strength of spillovers. Following Allen and Donaldson (2020) and Kline and Moretti (2014), we allow spillovers to operate with a one-period lag rather than contemporaneously. This functional form and the lag align with the specification of the spillover regression, where the lag reflects the time needed for knowledge to diffuse locally.

Adoption incurs fixed costs F^{T} in units of final goods (Buera et al., 2021). Firms adopt technology

[27] In one setup, 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 another, based on Desmet and Rossi-Hansberg (2014), own innovation costs are reduced as higher adopter shares facilitate knowledge transfers.

when the additional operating profits from adoption exceed the fixed costs:

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

where π_{it} is firm i's profit. Firms internalize the direct gains η (private returns from adoption) but not the spillovers $f(\lambda^T_{t-1})$, taking λ^T_{t-1} as given in period t. Due to this externality, social returns to adoption exceed private returns, leading to adoption rates below the socially optimal level. Only firms with ϕ_{it} higher than the following cutoff adopt technology:

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

The share of adopters is equivalent to the probability of adoption $\lambda^T_t = \mathbb{P}[\phi_{it} \geq \bar{\phi}_t]$, because the firm mass is normalized.

Equilibrium. In each period, given λ^T_{t-1}, firms make adoption decisions to maximize profits, and goods and factor markets clear (static equilibrium). The adopter share λ^T_t is a state variable that endogenously evolves based on these adoption decisions (dynamic equilibrium). Given λ^T_{t-1}, λ^T_t is determined in t, and then λ^T_{t+1} 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 is expressed as:

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

Combining equations (4.1) and (4.2), the equilibrium adopter share in each period, conditional on λ^T_{t-1}, L, η, and δ, can be expressed as:

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

where $\hat{\lambda}^T_t = \hat{\lambda}^T_t(\lambda^T_{t-1}; L, \eta, \delta)$ is implicitly defined by

$$\hat{\lambda}^T_t = \left[A(\hat{\lambda}^T_t)^{2-\sigma} \frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} f(\lambda^T_{t-1}) L \right]^{\frac{\theta}{\sigma-1}},$$

$$\text{where} \quad A(\lambda^T) = \left[\frac{\theta}{\theta - (\sigma - 1)} \left((\eta^{\sigma-1} - 1)(\lambda^T)^{\frac{\theta-(\sigma-1)}{\theta}} + 1 \right) \right]^{\frac{1}{\sigma-1}}, \quad f(\lambda^T) = \exp(\delta \lambda^T). \tag{4.4}$$

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

Equilibrium properties and multiple steady states. Assumption 1(i) ensures a unique static equilibrium in each period. Higher adopter shares generate two opposing general equilibrium forces: increased competition, which discourages adoption, and lower fixed adoption costs due to reduced P_t, which encourages it. Because firms do not internalize P_t, sufficiently low σ weakens the competition effect and strengthens the cost-reduction effect, generating complementarity and the potential for static multiple equilibria within each period.[28] However, by imposing $\sigma > 2$, the competition effect remains sufficiently strong, ruling out this possibility and ensuring a unique static equilibrium. Moreover, the equilibrium adopter share λ_t^T increases with higher values of η and δ, as they boost private returns and spillovers from adoption, respectively.

Because of the unique static equilibrium each period, given any initial adopter shares λ_{t_0}, there exists a unique sequence of static equilibria that forms a deterministic dynamic path from λ_{t_0} to a steady state. The dynamic path of λ_t^T exhibits dynamic complementarity in adoption, meaning λ_t^T increases with λ_{t-1}^T, consistent with the third empirical finding. The dynamic complementarity arises from the combination of spillovers and adoption costs in units of final goods. Spillovers raise all firms' productivity, lowering P_t and thus reducing total adoption costs $P_t F^T$, further encouraging adoption.[29] If either condition is not met, the complementarity does not emerge. In particular, if adoption costs are in units of labor instead of final goods, the complementarity fails to arise, regardless of strength of spillovers. This is because higher spillovers increase gains from adoption but also raise wages through increased labor demand, exactly offsetting the gains. Thus, assuming that adoption costs are in units of final goods is essential to reproduce the third empirical finding, as spillovers alone cannot reproduce this outcome (see Appendix C.3).

Importantly, we show that multiple steady states can arise from dynamic complementarity. In such a case, the initial adopter share determines which steady state will be realized in the long-run, implying path dependence. Also, they can be Pareto-ranked based on the 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) (Comparative statics) $\partial\lambda_t^T(\lambda_{t-1}^T; L, \eta, \delta)/\partial\eta \geq 0$ and $\partial\lambda_t^T(\lambda_{t-1}^T; L, \eta, \delta)/\partial\delta \geq 0$;

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

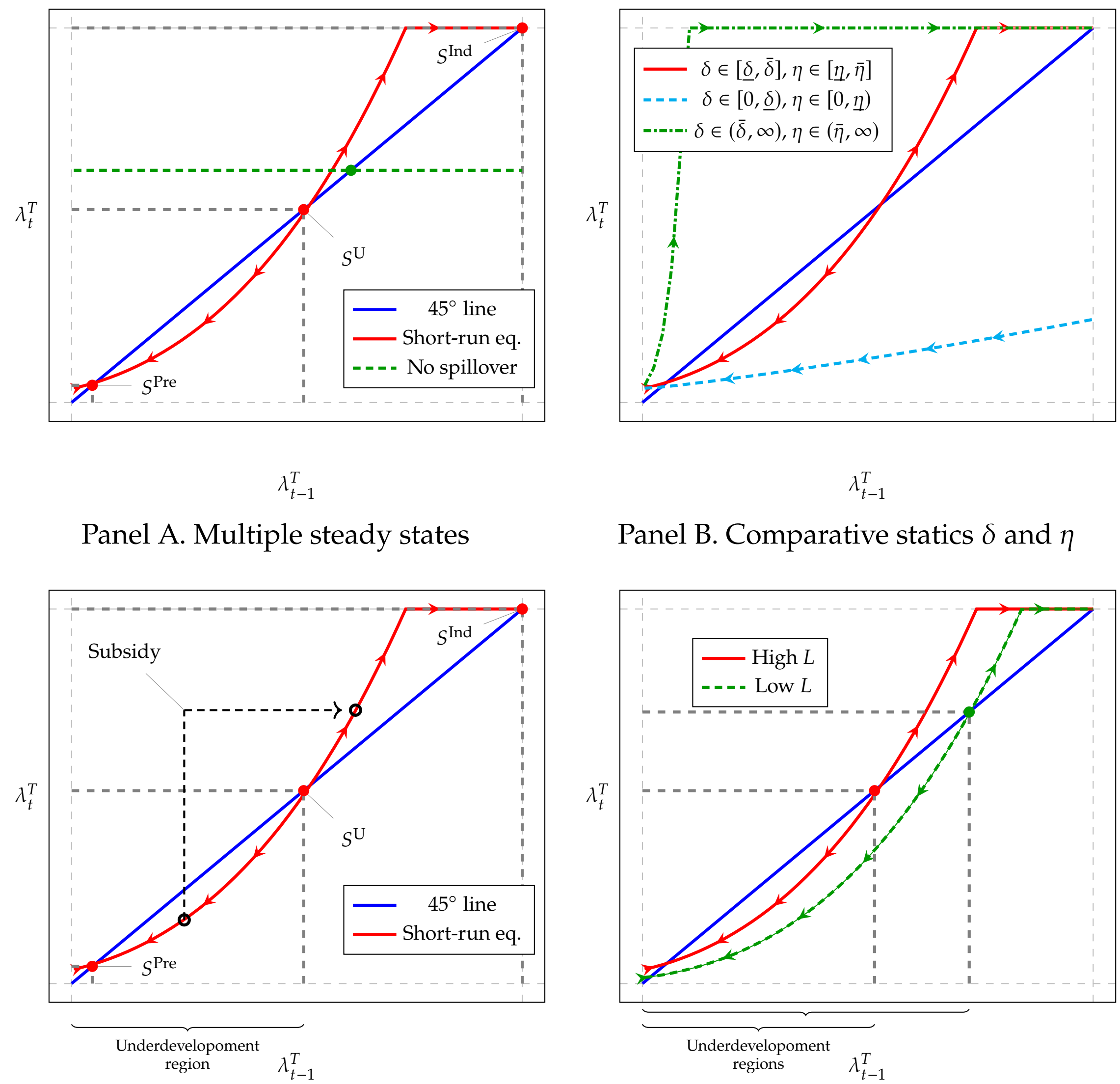
(iv) (Multiple steady states) There exists an interval $[\underline{\delta}, \bar{\delta}]$ (and $[\underline{\eta}, \bar{\eta}]$) such that holding other parameters constant, multiple steady states arise only for $\delta \in [\underline{\delta}, \bar{\delta}]$ (and $\eta \in [\underline{\eta}, \bar{\eta}]$);

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

[28] In equation (4.4), $A(\lambda_t^T)^{2-\sigma} = A(\lambda_t^T)^{1-\sigma}A(\lambda_t^T)$ reflects these two opposing effects: $A(\lambda_t^T)^{1-\sigma}$ captures the competition effect, and $A(\lambda_t^T)$ captures the cost-reduction effect. This kind of static multiple equilibria has been studied by Matsuyama (1995) and Buera et al. (2021).

[29] This cost-reduction channel of local spillovers is consistent with the case of POSCO, detailed in Appendix B.1.

Figure 3: Multiple Steady States and the Big Push



Panel A. Multiple steady states

Panel B. Comparative statics δ and η

Panel C. Big push

Panel D. Market size

Notes. Panel A shows that multiple steady states emerge when the short-run equilibrium curve exhibits sufficient nonlinearity and that there exists a unique steady state without spillovers. Panel B shows that multiple steady states arise only for medium ranges of η and δ. Panel C shows how a big push can shift an economy out of the "underdevelopment" region. Panel D shows that the size of the underdevelopment regions decreases with market size L.

The case of multiple steady states is illustrated in Panel A of Figure 3, which shows three distinct steady states with two basins of attraction. The red locus, defined by equation (4.3), represents short-run equilibrium adopter shares λ_t^T conditional on the previous period's λ_{t-1}^T. The equilibrium moves along the red locus as time passes. Steady states are determined at points where $\lambda_{t-1}^T = \lambda_t^T, \forall t$ holds, where the red locus intersects the 45-degree blue line. In this case, there are three intersection points (S^{Pre}, S^{U}, and S^{Ind}), corresponding to the pre-industrialized, unstable, and industrialized steady states, respectively. S^{U} is unstable. The economy converges to S^{U} only if the initial condition is exactly given by S^{U}, so it is excluded from our focus.

An initial adopter share $\lambda_{t_0}^T$ determines the long-run steady state. If $\lambda_{t_0}^T \in [0, S^{\mathrm{U}})$, the economy converges to S^{Pre}. If $\lambda_{t_0}^T \in (S^{\mathrm{U}}, 1]$, it converges to S^{Ind}. These steady states can be Pareto-ranked based on their adopter shares, with S^{Ind} being Pareto-dominant as more firms adopt technology there. The nonlinearity of the red locus, induced by spillovers, is essential for generating multiple steady states. Without spillovers ($\delta = 0$), the equilibrium adopter share is independent of the previous period's share, leading to a unique steady state, indicated by the single intersection of the green dashed horizontal line and the 45-degree line.

The functional form of $f(\lambda_{t-1}^T)$ is crucial in determining the potential for multiple steady states, as its strict convexity ensures the strict convexity of λ_t^T with respect to λ_{t-1}^T. However, this outcome generalizes to any functional forms with strict convexity. With the current exponential form, there can be at most three steady states, while alternative functional forms with more complex nonlinearity in the short-run equilibrium curve could result in more than three.

Comparative statics of $\boldsymbol{\delta}$ and $\boldsymbol{\eta}$. The existence of multiple steady states depends on the two key parameters, δ and η (Proposition 1(iv)). They arise only within medium ranges of $\delta \in [\underline{\delta}, \bar{\delta}]$ and $\eta \in [\underline{\eta}, \bar{\eta}]$, where spillovers or direct productivity gains are neither too strong nor too weak (Panel B). If δ (or η) is too high or too low, spillovers (or private returns) become excessively large or small, resulting in either too many or too few adopters, leading to a single steady state.

Big push and market size. If an initial condition is trapped in the "underdevelopment" region $[0, S^{\mathrm{U}})$, a big push policy that provides a one-time subsidy for adopters' input or adoption costs can have permanent effects by moving the economy out of this region (Panel C). Permanent effects are only possible with multiple steady states; with a unique steady state, the subsidy would merely shift the short-run equilibrium temporarily, and the economy would revert to its original steady state once the subsidy ends. Ceteris paribus, the underdevelopment region shrinks with larger market size L, making the big push more likely to occur (Panel D), because the gains from adoption increase with firms' scale (e.g., Yeaple, 2005; Bustos, 2011). These are summarized in Proposition 2.

Proposition 2. *Suppose the multiple steady states exist and the economy is initially in the "underdevelopment" region, $\lambda_{t_0}^T \in [0, S^U)$:*
(i) (Big push) There exists a threshold $\underline{s}$ such that a one-time subsidy for adopters' input costs or fixed adoption costs that satisfies $s_t > \underline{s}$ can move the economy out of the underdevelopment region;
(ii) (Market size) The underdevelopment region and threshold subsidy level decrease with market size L, i.e., $\partial S^U / \partial L < 0$ and $\partial \underline{s} / \partial L < 0$.

5. Quantification

5.1 Quantitative Model

We extend the simple model in the previous section and develop a quantitative framework to evaluate the big push episode. Additional details are provided in Appendix D.

Geography, sectors, and trade. We divide the world into Home and Foreign (H and F), where Home is a small open economy taking Foreign aggregates as given. Home consists of 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's variety is tradable across both regions and countries, subject to import tariffs t_{jt} and iceberg costs $\tau_{nmj} \geq 1$ for internal trade and $\tau^x_{nj} \geq 1$ for international trade.

In each region, there is a competitive labor market. Households are immobile and supply labor inelastically. Later, we extend the model to incorporate spatial mobility of labor as a robustness check

In each region-sector, a fixed mass of monopolistically competitive firms (M_{nj}) and perfectly competitive final goods producers aggregate available varieties from Home and Foreign using a CES aggregator, producing nontradable local aggregates (Q_{njt}) for final consumption and intermediate inputs. The price index is given by

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

where p_{injt} is the price charged by firms, and Ω_{mj} is the set of available sector j varieties in region m. With no fixed export costs for internal trade, the same set of varieties is available in all Home regions. P^f_{jt} is exogenous Foreign import price.

Home firms face the demand schedule $p_{it}^{-\sigma} D^x_{jt}$, where D^x_{jt} is exogenous Foreign demand. It captures Foreign market size along with any common export barriers. Exporters incur fixed export costs F^x_j in units of labor. Unlike adoption costs, fixed export costs do not exhibit dynamic complementarity since they are not in units of final goods.

Production. Firms have the following Cobb-Douglas production function:

$$y_{it} = z_{it} L_{it}^{\gamma^L_j} \prod_k (M^k_{it})^{\gamma^k_j}, \qquad \gamma^L_j + \sum_k \gamma^k_j = 1,$$

where L_{it} denotes labor inputs, and M^k_{it} sector k intermediate inputs. The productivity term z_{it} is composed of three components as in the simple model: $z_{it} = \eta^{T_{it}} f(\lambda^T_{nj,t-1}) \phi_{it}$. The spillovers $f(\lambda^T_{nj,t-1})$ increase with the previous period's regional-sector adopter shares $\lambda^T_{nj,t-1}$, and ϕ_{it} follows a bounded Pareto distribution:

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

parametrized by $\phi^{\min}_{njt}$, κ, and θ. The unbounded Pareto is the limiting case of the bounded Pareto, which can be achieved by letting $\kappa \to \infty$. The lower bound of the distribution ($\phi^{\min}_{njt}$) varies by regions, sectors, and periods, while the upper bound ($\kappa\phi^{\min}_{njt}$) is proportional to the lower bound by a factor of κ. This bounded Pareto distribution rationalizes regions with zero adoption in the data: if the adoption cutoff exceeds $\kappa\phi^{\min}_{njt}$, no firms adopt. $\phi^{\min}_{njt}$ captures each region-sector's productivity shifters that cannot be explained by adoption, such as the construction of industrial complexes.

Adoption cost and subsidy. Fixed adoption costs have a Cobb-Douglas form:

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

where F^T is a parameter that governs the overall cost level. We assign Cobb-Douglas shares (γ_j^L and γ_j^k) identical to those in the production function due to limited data on intermediate goods used in adoption costs. Because parts of adoption costs are in units of final goods, dynamic complementarity still arises. Cost minimization implies that total expenditures on adoption costs are given by $c_{njt}F^T$, where c_{njt} is unit costs of input bundles: $c_{njt} \propto w_{nt}^{\gamma_j^L} \times \prod_k P_{njt}^{\gamma_j^k}$.

We model adoption subsidies as input subsidies $0 \leq s_{njt} \leq 1$, varying across regions, sectors, and periods.[30] With these subsidies, adopters' unit costs of production become $(1 - s_{njt})c_{njt}/z_{it}$. The government finances these subsidies through a common labor tax τ_t^w.[31] The government budget is balanced each period.

Preference. Representative households have Cobb-Douglas preferences over consumption in each sector: $\ln\left(\prod_{j=1}^J C_{njt}^{\alpha_j}\right)$. The budget constraint is $\sum_{j=1}^J P_{njt}C_{njt} = (1 - \tau_t^w + \bar{\pi}_t)w_{nt}$. Their total income consists of after-tax wages $(1-\tau_t^w)w_{nt}$ and dividend income $\bar{\pi}_t w_{nt}$, where total profits and government spending are distributed across households proportional to their labor incomes.

Equilibrium. In the equilibrium, given initial conditions $\{\lambda^T_{nj,-1}, L_{n1}\}$ and paths of the fundamentals $\{\phi^{\min}_{njt}, P^f_{jt}, D^x_{jt}\}$, tariffs $\{t_{jt}\}$, and subsidies $\{s_{njt}\}$, firms maximize profits; households maximize utility; labor and goods markets clear; trade is balanced; the government budget is balanced; and firm adoption decisions determine a path of the state variable $\{\lambda^T_{njt}\}$.

5.1.1 Discussion

Firm Scale, Market Access, and the Big Push. Higher trade costs, or smaller foreign demand, limit firms' ability to sell products in other regions or countries, reducing their market size. Higher trade costs also increase their costs of intermediate inputs and adoption. Consequently, they reduce firms'

[30] During the HCI Drive, the Korean government provided subsidies to adopters for purchases of capital equipment related to adopted technologies. In the model, we interpret new capital equipment as intermediate inputs and these subsidies as input subsidies for adopters.

[31] This assumption is based on the 1970s pro-business labor market policies, where nominal wage growth was restricted, and labor union activities were prohibited to promote the HCI Drive (Kim and Topel, 1995; Itskhoki and Moll, 2019).

scale and diminish their gains from adoption, making it a big push more difficult to be achieved. This implication is consistent with the heterogeneous effects of complementarity (Table 4) and aligns with the prediction from the simple model (Proposition 2(ii)).

Implication of international trade on industrialization. Due to the Cobb-Douglas production and utility functions, consumers and firms allocate constant fractions of expenditures across sectors. In a closed economy (the limiting case of an open economy achieved by letting $P^f_{jt} \to \infty$ and $D^x_{jt} \to 0$), the heavy manufacturing sector's GDP shares remain constant across steady states, even if the big push leads to higher adoption levels. In a small open economy, however, higher productivity in heavy manufacturing strengthens comparative advantage in this sector, increasing its exports. Its GDP shares rise in the industrialized steady state due to these increased exports. Therefore, in this setup, industrialization relates to changes in comparative advantage induced by adoption.

Relationships to the recent big push models. We compare our model to those recently developed by Buera et al. (2021) and Kline and Moretti (2014). First, similar to Buera et al. (2021), the use of final goods for adoption costs is a source of multiplicity, as detailed in Appendix C.3. However, the spillovers, absent in their model, combined with this feature, creates the potential for multiple steady states in our model. While Buera et al. (2021) explore how idiosyncratic distortions and intermediate input intensities amplify effects of a big push in a closed economy setup, we extend their model to an open economy with rich spatial interactions and show that market access amplifies a big push. Second, in the model of Kline and Moretti (2014), multiple steady states arise from migration and agglomeration, as people move to more productive regions, enhancing productivity through agglomeration. In our model, labor is immobile, shutting down this channel.

5.2 Counterfactual

How would the economy have evolved differently without the big push? We construct a counterfactual economy without the big push, where the government does not provide temporary subsidies for adoption, corresponding to setting $s_{njt} = 0$, and calculate the heavy manufacturing sector's GDP shares and welfare changes under this scenario.

5.3 Taking the Model to the Data

Each period in the model corresponds to 4 years of the data. Sectors are classified into four broad groups: commodity, light manufacturing, heavy manufacturing, and service. The first three are tradable both internally and internationally, whereas the service is nontradable across regions and countries. Since the majority of adoption occurred in the heavy manufacturing sectors, we assume that adoption is only available within this sector. We calibrate the model to the years of 1972, 1976, and 1980, corresponding to $t = 1, 2, 3$. After $t = 3$, fundamentals are held constant at the 1980 levels. Given the initial adopter shares $\lambda^T_{nj,68}$ and population $L_{n,72}$ taken directly from the data, we solve the model

Table 5: Calibration

	Description	Value	Identification / Moments
		External calibration	
η	Direct productivity gains	1.35	Winners vs. losers, Table 2
δ	Spillover semi-elasticity	0.90	Spillover estimate, Table 3
σ	Elasticity of substitution	4	Literature
θ	Pareto shape parameter	3.18	Axtell (2001)
ξ	Distance trade cost elasticity	0.43	Monte et al. (2018)
α_j	Preferences	0.05–0.47	IO table
γ_j^k	Production	0–0.47	IO table
M_{nj}	Exogenous firm mass	0–0.05	Value added (Chaney, 2008)
		Internal calibration	
F^T	Fixed adoption cost	0.0002	Avg. adopter shares, 72
F_j^x	Fixed export cost, light mfg.	0.60	Exporter share, light mfg.
F_j^x	Fixed export cost, heavy mfg.	0.055	Exporter share, heavy mfg.
κ	Pareto upper bound	1.519	Share of regions with adoption
$\bar{s}$	Subsidy rate	0.081	Avg. adopter shares, 76 and 80

Notes. This table reports the calibrated parameters of the model, their values, and the moments used to identify them.

for $t = 1$ and obtain the equilibrium values of λ_{nj1} and continue this process period by period until the model converges to steady states.[32]

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

$$\mathbf{\Theta}^{\mathrm{E}} = \{\eta, \delta, M_{nj}, \theta, \sigma, \gamma_j^L, \gamma_j^k, \tau_{nmj}, \tau_{nj}^x, \alpha_j\} \qquad \text{and} \qquad \mathbf{\Theta}^{\mathrm{M}} = \{\kappa, F_j^x, F^T\}.$$

$\mathbf{\Theta}^{\mathrm{E}}$ and t_{jt} are externally calibrated, while s_{njt}, $\mathbf{\Psi}_t$, and $\mathbf{\Theta}^{\mathrm{M}}$ are internally calibrated via indirect inference. Table 5 summarizes our calibration procedure, with details in Appendix E.1.

5.3.1 External Calibration

Elasticity of substitution and technology adoption. We set the elasticity of substitution σ to 4, as standard in the literature. By taking the log of adopters' sales in the model, we derive:

$$\ln \mathrm{Sale}_{it} = (\sigma - 1) \ln \eta \times T_{it} + \delta_{mt} + (\sigma - 1) \ln \phi_{it},$$

which can be mapped to the winners vs. losers specification. Fixed effects δ_{mt} absorb out variables common at the match levels, including local spillovers, unit costs of production, and market size common across firms within region-sectors. From this mapping, we set $\eta = \exp(0.9/(\sigma - 1)) = 1.35$,

[32] While our firm balance sheet data covers the period from 1970 to 1982, technology adoption contracts span from 1962 to 1988. Using the information on the start year of firms, we construct the adopter shares for 1968.

where 0.9 corresponds to the pooled diff-in-diff estimate in Panel B of Table 2. Note that based on the lack of evidence that winners received more subsidies than losers, we map the estimates to the pure direct effects of adoption, and assume that subsidies are absorbed into δ_{mt}.[33]

For non-adopters, taking the log of sales gives:

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

which can be mapped to the spillover regression. $\mathbf{X}_{njt}$ includes region-sector variables, such as unit cost and market access terms. From this relationship, we pin down δ to be $2.7/(\sigma-1) = 0.9$, where 2.7 corresponds to the average of the IV estimates from Panel A of Table 3. The baseline calibrated values for η and δ are lower bounds among the possible mappings.[34]

Import tariffs and iceberg trade costs. Import tariffs are taken directly from the data. Internal iceberg costs are parametrized as $\tau_{nmj} = (\text{Dist}_{nm})^{\xi}$, where Dist_{nm} is the distance between regions n and m. The elasticity ξ is set to $\xi = 1.29/(\sigma - 1)$ for tradable sectors following Monte et al. (2018). The bilateral distance matrix incorporates impacts of the Gyeongbu Expressway, which reduced travel times between connected regions by 66%, as reported by the Ministry of Land, Infrastructure, and Transport.[35] Distances between connected regions are assigned with 66% lower values, and the Dijkstra algorithm is applied to calculate the fastest routes. When exporting, firms have to ship their products to the nearest port and pay both iceberg and fixed export costs. International iceberg costs are parametrized as $\tau^{x}_{nj} = (\text{Dist}^{\text{port}}_{n})^{\xi}$, where $\text{Dist}^{\text{port}}_{n}$ is the distance to the nearest port. The same Dijkstra algorithm is applied, and τ^{x}_{nj} is set to 1 for regions that have ports.

The remaining parameters. The Pareto shape parameter θ is set to $1.06 \times (\sigma - 1)$ (Axtell, 2001; di Giovanni et al., 2011). M_{nj} is set proportional to the 1972 GDP share of each region-sector, with $\sum_{n,j} M_{nj} = 1$ (Chaney, 2008). This is just a normalization because M_{nj} is not separately identifiable from natural advantages $\phi^{\min}_{njt}$ under the fixed entry. The Cobb-Douglas shares of preferences and production (α_j, γ^{k}_{j}, and γ^{L}_{j}) are taken from the input-output tables.

5.3.2 Internal Calibration

Adoption subsidy. Adoption subsidies are provided in $t = 2, 3$ (corresponding to 1976 and 1980). They are allocated to firms in regions with at least one firm that ever received directed credit in the data, denoted as $\mathcal{N}^{s}$ that includes 35 regions out of 86. We assume the same subsidy level $\bar{s}$ across

[33]If winners had received more subsidies, the sales estimates would be mapped to the joint effects $(\sigma-1)\ln\eta/(1-s_{it})$.

[34]An alternative mapping using $\text{TFPR}_{it} \propto (\sigma-1)/\sigma \ln z_{it}$ (Blackwood et al., 2021) gives larger values: $\eta = 3.3$ and $\delta = 2.7$, calculated as $\eta = \exp(\sigma/(\sigma-1) \times 0.9)$ and $\delta = \sigma/(\sigma-1) \times 2$, with 0.9 based on the winners vs. losers pooled diff-in-diff estimate for TFPR_{it} (Panel B of Table 2) and 2 from the IV spillover estimates for TFPR_{it} (Panel B of Table 3).

[35]This 66% reduction is consistent with Jaworski and Kitchens (2019), who assume speeds of 10 miles per hour on unpaved roads and 45 miles per hour on paved state highways in the US.

these regions and periods:

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

Constrained minimum distance. We calibrate $\mathbf{\Theta}^{\text{M}}$, $\bar{s}$, and $\mathbf{\Psi}_t$ by solving the following constrained minimization problem:

$$\{\hat{\mathbf{\Theta}}^{\text{M}}, \hat{\bar{s}}\} \equiv \arg\min_{\{\mathbf{\Theta}^{\text{M}},\bar{s}\}} \left\{ \left(\mathbf{m}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{m}\right)' \left(\mathbf{m}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{m}\right) \right\} \qquad \text{s.t.} \qquad \mathbf{C}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{C} = \mathbf{0}. \tag{5.1}$$

We minimize the distance between the model moments $\mathbf{m}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)$ and the data moments $\mathbf{m}$ subject to the constraints $\mathbf{C}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t) - \mathbf{C} = \mathbf{0}$. The moments are normalized to express their differences as percentages. The constraints ensure that the model variables $\mathbf{C}(\mathbf{\Theta}^{\text{M}}, \bar{s}, \mathbf{\Psi}_t)$ match the corresponding data variables $\mathbf{C}$.

We choose moments that are informative about the underlying parameters. The average adopter shares across regions in 1972 identify F^T, while the average adopter shares in 1976 and 1980 identify $\bar{s}$. Conditional on η and δ, increases in adopter shares in 1976 and 1980 relative to the 1972 level indicate the effects of subsidies, as $\bar{s}$ only influences the periods when subsidies are applied. The share of regions with zero adoption identifies κ, as lower κ increases the likelihood that the cutoff adoption productivity exceeds the Pareto upper bound. We calibrate the export fixed costs F_j^x for the light and heavy manufacturing sectors using the average regional exporter shares. Since no firm-level data is available for the commodity sector, we set its F_j^x equal to that of the light manufacturing sector.

Conditional on $\mathbf{\Theta}^{\text{M}}$ and $\bar{s}$, the fundamentals $\mathbf{\Psi}_t$ are identified by the imposed constraints that match sectoral export intensities, sectoral import shares, regional gross output distributions, sectoral producer price indices (PPI) growth, and aggregate real GDP growth. By imposing these constraints, the model matches these variables to the data for the years 1972, 1976, and 1980. D_{jt}^x are identified by the export intensities and P_{jt}^f by the import shares; and $\phi_{njt}^{\min}$ by the regional output distributions, sectoral PPI growth, and aggregate real GDP growth. Trade deficits are treated as exogenous, as standard in the international trade literature.

5.3.3 Estimation Results

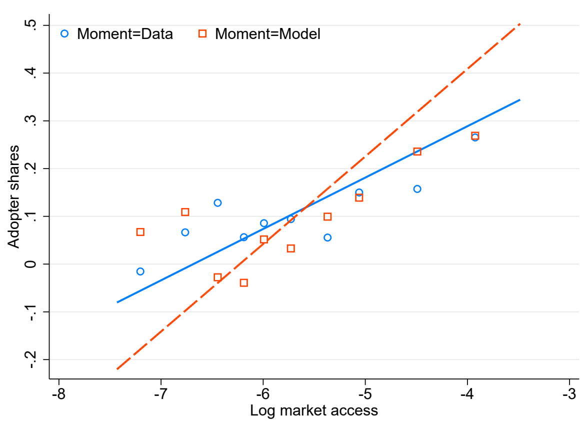
Targeted moments. We internally calibrate 5 parameters to match 6 targeted moments. The model moments closely match their data counterparts (Table 6). The estimated subsidy rate is 8.1%, implying that adopters are subsidized with 8.1% of their input expenditures. In 1976 and 1980, 1.35% and 1.40% of GDP, respectively, are spent on adoption subsidies. Fixed adoption costs in the heavy manufacturing sector were higher than fixed export costs. On average, total adoption costs ($\sum_n F^T c_{njt}$) are 35.1 times larger than total fixed export costs ($\sum_n F_j^x w_{nt}$).

Table 6: Model Fit

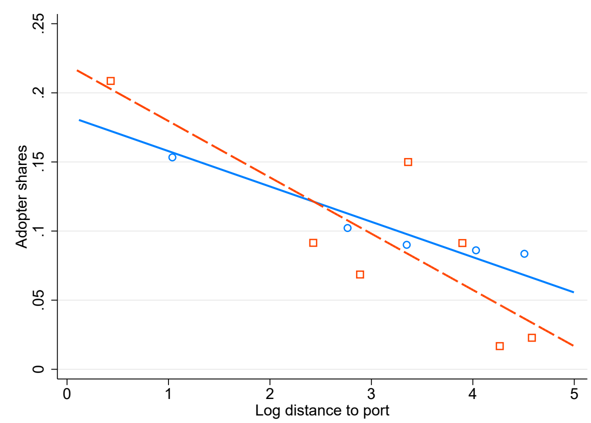
Moment	Model	Data
Avg. $\{\lambda^{x}_{njt}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$, light mfg.	0.29	0.28
Avg. $\{\lambda^{x}_{njt}\}_{n\in\mathcal{N},t\in\{72,76,80\}}$, heavy mfg.	0.19	0.19
Avg. $\{\lambda^{T}_{nj,72}\}_{n\in\mathcal{N}}$	0.07	0.07
Avg. $\{\lambda^{T}_{nj,76}\}_{n\in\mathcal{N}}$	0.10	0.09
Avg. $\{\lambda^{T}_{nj,80}\}_{n\in\mathcal{N}}$	0.11	0.15
Avg. shares of regions with positive adoption	0.54	0.47

Notes. This table presents the fit of the model.

Figure 4: Non-targeted Moments. Adopter Shares and Market Access



A. Market access



B. Distance to port

Notes. Panels A and B illustrate binscatter plots of market access (equation (3.7)) and log distance to port (a proxy for export costs) versus adopter shares in both the model and the data, respectively. Each circle represents the average values of these two variables within bins that are optimally selected following Cattaneo et al. (2024).

Non-targeted moments. We present three non-targeted moments that validate the model. First, as shown in Figure 4, the model captures a positive relationship between adopter shares and market access and a negative relationship between adopter shares and the distance to port, a proxy for export barriers. These non-targeted moments are consistent with the stronger complementarity observed with larger market access. Second, regional distributions of the heavy manufacturing sector's employment, export, and shares of exporters are not directly targeted in the estimation, but the calibrated model qualitatively and quantitatively captures systematic positive relationships between these variables and adopter shares (Appendix Table E1). Finally, the model captures trajectories of aggregate employment shares between 1972-1980 quite well (Panel C of Figure 5).

The assumptions of static adoption decisions. The assumptions of the static adoption decisions make the state variable backward-looking. This simplification helps preserve rich spatial heterogeneity and connect the model to the empirical findings while facilitating computational implementation.[36] However, if adoption costs were sunk rather than fixed, adoption decisions would be forward-looking and depend on the entire path of future variables. Even so, dynamic complementarity could still lead to multiple steady states, as studied by Alvarez et al. (2023). Targeting the same path of state variables and static equilibrium outcomes in a forward-looking model with multiple steady states would not change our results qualitatively because the static equilibrium outcomes remain the same. However, welfare effects and magnitude of the quantitative results might differ.

6. Quantitative Results

6.1 Aggregate and Local Effects of the Big Push

Industrialization. Figure 5 displays the time paths of the heavy manufacturing sector's GDP shares, export intensities, and employment shares for both the baseline economy with subsidies and the counterfactual economy without them. Table 7 reports the steady state differences in these variables between the two economies. The counterfactual economy converges to a less-industrialized steady state, with the heavy manufacturing GDP share decreasing by 8.6% (1.95 percentage points), export intensity by 16.2% (3.33 percentage points), and employment share by 9.6% (0.68 percentage point) compared to the baseline. In both economies, it takes about 24 years (6 periods) to reach the steady states after 1980.

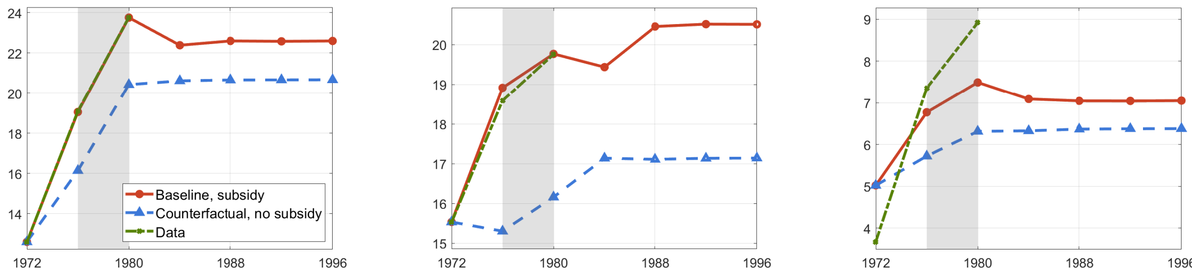
At the local level, industrialization patterns exhibit substantial heterogeneity. The steady state differences in heavy manufacturing GDP shares, export intensities, and employment shares across regions range from −1.43% to 52.93%, −7.92% to 3.45%, and 0.68% to 10%, respectively. Only four regions experience higher heavy manufacturing GDP shares in the baseline compared to the counterfactual, driven by increased productivity due to technology adoption (Appendix Figure E1). These productivity improvements in the four regions reduce heavy manufacturing shares in other regions by increasing competition, leading to divergence between these regions and the others. These results suggest that aggregate industrialization is driven by localized productivity improvements of a few regions, rather than by uniform growth across the entire country.

Welfare. We compute each region's consumption-equivalent welfare changes equating discounted utilities in the counterfactual to those in the baseline and calculate aggregate welfare changes as population-weighted regional welfare changes.[37] We use a discount factor of $0.85(= 0.96^4)$. The big push increases aggregate welfare by 1.27%, but with notable distributional consequences across regions, ranging from −1.44% to 37.52% (col. 4 of Table 7). Not all regions benefit from the big push:

[36] For example, Desmet and Rossi-Hansberg (2014), Arkolakis et al. (2019), Peters (2022), and Nagy (2023) similarly simplify agents' forward-looking decisions to make models more tractable while preserving spatial complexity.

[37] Specifically, we compute ω_n such that satisfy $\sum_t \beta^\tau \ln C_{nt} = \sum_t \beta^\tau \ln(1+\omega_n)C^c_{nt}$, where β is the discount factor and C^c_{nt} is consumption in the counterfactual. The aggregate welfare changes are calculated as $\sum_n \frac{L_{nt_0}}{\sum_m L_{mt_0}} \omega_n$.

Figure 5: Aggregate Effects of the Big Push. Baseline vs. Counterfactual



A. GDP share (%) | Heavy manufacturing B. Export intensity (%) | C. Emp. share (%)

Notes. Panels A, B, and C illustrate the heavy manufacturing sector's GDP shares, export intensities, and employment shares of the baseline and counterfactual economies. The gray-shaded areas represent the policy periods during which subsidies were provided (1976 and 1980). The green solid line represents the data from the input-output tables, while the red dotted and blue dashed lines represent outcomes of the baseline and counterfactual economies, respectively.

Table 7: Aggregate and Local Effects of the Big Push. Baseline vs. Counterfactual

Steady state differences (Baseline vs. counterfactual)	ΔGDP share (p.p) (1)	ΔExport intensity (p.p) (2)	ΔEmp share (p.p) (3)	ΔWelfare (%) (4)
Aggregate level	1.95	3.33	0.68	1.27
Local level	$[-1.43, 52.93]$	$[-7.92, 3.45]$	$[0.68, 10]$	$[-1.44, 37.52]$

Notes.This table reports counterfactual results. The first row reports steady state differences in the heavy manufacturing sector's GDP shares, export intensities, and employment shares, and welfare changes between the baseline and counterfactual economies at the aggregate level. The second row reports ranges of these differences and welfare changes at the local level.

66 out of 86 regions experience welfare gains, while remaining 20 regions see welfare losses (see Appendix Figure E2 for the distribution of the welfare effects). These distributional effects arise due to two opposing forces from the localized productivity improvements. On the one hand, consumers and producers in other regions benefit from lower prices via internal trade linkages. On the other hand, increased domestic competition reduces their profits.

6.2 Firm Scale, Market Access, and the Big Push

We examine how factors that increase firms' scale amplify the big push. We temporarily adjust foreign demand, import tariffs, and internal trade costs only during the policy periods (1976 and 1980), while keeping their post-1980 levels unchanged. These adjustments are intentionally applied only in 1976 and 1980 to focus on their interaction with the big push. The results are reported in Table 8.

Larger foreign demand increases firms' scale. Between 1972 and 1980, estimated foreign demand rose by 48% relative to total domestic demand—which can be driven by, for example, government-led export promotion, increased world demand, and reduced trade costs. In a scenario where foreign demand remains at the 1972 level in 1976 and 1980, the steady state differences in heavy manufacturing

Table 8: The Effects of the Big Push under Alternative Scenarios for Market Access and Other Policies

Baseline (1)	Lower foreign demand (2)	Higher tariffs (3)	No highway (4)	No internal trade (5)	Joint (2 + 3 + 4) (6)
Δ Heavy mfg. GDP shares (p.p)					
1.95	0.25	1.91	1.71	0	0
Δ Aggregate welfare (%)					
1.27	0.43	1.14	0.90	0	0.31
Does the big push occur?					
Y	Y	Y	Y	N	N

Notes. This table presents the results of quantitative exercises where various spatial elements and other policies are temporarily adjusted during the policy periods (1976 and 1980), while their post-1980 levels remain unchanged. Column 2 considers a scenario where foreign demand is held constant at the 1972 level. Column 3 examines the impact of a protectionist tariff scheme, where tariffs increase by 40% between 1972 and 1980. Column 4 reverses the 66% reduction in travel time resulting from the highway construction. Column 5 explores the impact of prohibiting internal trade within the heavy manufacturing sector. Finally, column 6 considers the joint effects of the scenarios in columns 2, 3, and 4. Appendix Figure E3 presents the time paths of heavy manufacturing GDP shares under different scenarios.

GDP shares and welfare gains are 0.25 percentage points and 0.43%, respectively—both smaller than the baseline (col. 2).

We next examine the role of import tariffs. Higher tariffs can reduce foreign competition, but they also raise the cost of imported intermediate inputs, decreasing firms' scale. Between 1972 and 1980, the average import tariff rates for the heavy manufacturing sector dropped by 40%, from 38.4% to 23.4%. In a hypothetical protectionist scenario where tariff rates increase by 40% (rather than decrease as they did in reality), the benefits of reduced competition are outweighed by the increased production and adoption costs, resulting in weaker effects of the big push (col. 3).

The baseline calibration assumes that the construction of the highway in 1970 reduced travel times by 66%. Without the construction, reversing the 66% reductions, the big push has weaker effects (col. 4). Furthermore, if internal trade within the heavy manufacturing sector is completely shut down, the big push does not occur (col. 5).

Finally, we examine the combined effect of three adverse scenarios: lower foreign demand, protectionist tariffs, and the absence of highway construction. While the big push occurs in each individual scenario, it fails when all three scenarios are combined (col. 6).

These exercises highlight how various elements and other policies interact with the big push by influencing firms' scale. When they increase firms' scale, the big push becomes more effective and more likely to succeed. Importantly, had the government pursued protectionist policies—such as avoiding export promotion and raising tariffs—the Korean economy might not have achieved the industrialization. This finding contributes to the longstanding debate on whether Korea's economic success was driven by export-oriented trade policies (e.g., Krueger, 1997) or government-led industrial policies (e.g., Amsden, 1989). Our results suggest that these policies were, in fact, complementary.

6.3 Alternative Policy Schemes

Alternative subsidized regions. To examine the role of regional characteristics, we re-run the analysis while randomly selecting 35 subsidized regions out of 86—the same number as in the main exercise—and applying the same subsidy rate. We simulate this process 1,000 times. Among four variables—log distance to port, population, market access, and natural advantage—only distance to port and market access are significantly positively correlated with steady state differences in heavy manufacturing GDP shares and welfare changes across simulations (Appendix Table E2). These results re-emphasize the role of market access.[38]

General subsidy. Would the big push occur if the government provided general subsidies at an 8.1% rate—the same rate as in the main exercise—to all heavy manufacturing firms in the subsidized regions, regardless of their adoption activities? We find that these general subsidies do not lead to the big push, with smaller welfare gains at just 0.29% (Appendix Figure E4). The is because such subsidies reduce production costs for all firms, increasing domestic competition and lowering adoption incentives for firms that might have otherwise adopted technologies. This highlights that industrial policy should focus on addressing coordination failures, rather than distributing funds without targeted goals.[39]

Optimal subsidy rate. The calibrated subsidies are not necessarily optimal, leaving room for potential welfare improvements.[40] We numerically search for the optimal subsidy rate that maximizes aggregate welfare, conditional on the same set of subsidized regions. We find that an optimal rate of 12% yields welfare gains of 2%, a 0.78 percentage point higher than the baseline rate, and leads to a different steady state with even higher heavy manufacturing GDP shares than the steady state attained under the baseline rate (Appendix Figure E5).[41]

6.4 Additional Robustness Checks

Statistical uncertainty. The main calibration uses point estimates of $(\sigma-1)\eta$ and $(\sigma-1)\delta$ without accounting for their statistical uncertainties. To assess sensitivity to these uncertainties, we consider a wide range of values within their 95% confidence intervals and re-calibrate the remaining parameters and fundamentals for each value.[42] Within these intervals, one-time subsidies lead to the big push

[38] Specifically, we run the following regression using 1,000 simulations: $y_b = \bar{\mathbf{X}}_b'\boldsymbol{\beta} + \varepsilon_b$, where $\bar{\mathbf{X}}_b = \frac{1}{|\mathcal{N}_b^s|}\sum_{n\in\mathcal{N}_b^s}\mathbf{X}_{n,72}$, $\bar{\mathbf{X}}_b$ is the average of observables $\mathbf{X}_{n,72}$ across the subsidized regions, and $\mathcal{N}_b^s$ is the set of 35 subsidized regions in simulation b.

[39] This result aligns with Buera and Trachter (2024), who show that adoption subsidies are more cost-effective than general revenue subsidies.

[40] Deriving the optimal subsidy analytically in an economy with multiple steady states is beyond the scope of this paper. For optimal policy in static spatial frameworks, see Bartelme et al. (forthcoming), Fajgelbaum and Gaubert (2020), and Lashkaripour and Lugovskyy (2023).

[41] Unlike the simple model, which has at most three steady states, the quantitative model may admit more than three due to more complex spatial interactions (Allen and Donaldson, 2020).

[42] Allen and Donaldson (2020) conduct similar exercises to assess robustness for statistical uncertainties associated with estimated parameters. An alternative approach is bootstrapping both the regression and quantitative analyses, as in Fan et

only for medium ranges of their values (Appendix Table E3), but not for all values. As a result, it is difficult to conclude that the big push arises with the 95% statistical significance. However, this outcome aligns with the theoretical prediction from the simple model, where multiple steady states emerge only within medium ranges of η and δ. Specifically, for values of $(\sigma - 1)\delta$ below 1.70 (1.5 standard deviations lower than the baseline), the subsidies do not result in the big push. Similarly, for $(\sigma - 1)\eta$, the big push occurs only in the lower half of the 95% confidence interval and fails to arise for values above 1.2 (0.5 standard deviation higher than the baseline value).

Spatial mobility. We extend the model to incorporate myopic migration decisions of households as in Peters (2022). Appendix E.2 provides detailed explanations of the extension and its calibration procedure. Migration amplifies the big push, as labor relocates to regions with higher adoption levels, thereby reducing production and adoption costs in those regions (col. 1 of Appendix Table E4).

Alternative parameter values. We explore alternative values for σ and θ (col. 3-6 of Appendix Table E4). Lower σ amplifies the effects because our estimates do not separately identify η or δ from σ and both increase with lower σ. Lower θ also increases the effects, as they reduce dispersion in productivity. This results in a larger mass of firms being concentrated just below the cutoff, causing more firms to be affected by shifts in the cutoff due to subsidies.

7. Conclusion

We empirically and quantitatively explore the possibility of industrialization through a big push for technology adoption. We provide three empirical findings consistent with the big push narrative: direct effects on adopters, local spillovers, and local complementarity in adoption. We develop a model that allows for the potential for multiple steady states and a big push. Calibrating this model to the microdata and the causal estimates, we analyze the actual big push episode in South Korea. Our finding suggests that, without this intervention, the economy could have converged to a less-industrialized steady state. Moreover, market access played a quantitatively significant role in enabling the big push.

Our study highlights the importance of addressing coordination failures to facilitate the diffusion of advanced technologies in developing economies. Also, it suggests that policies should focus not only on coordination failures but also on ensuring sufficient market access for sustainable industrial growth.

al. (2023) and Choi and Levchenko (2024). However, because the point estimates of η and δ come from different sources of variation in the data, we cannot apply this bootstrap procedure.

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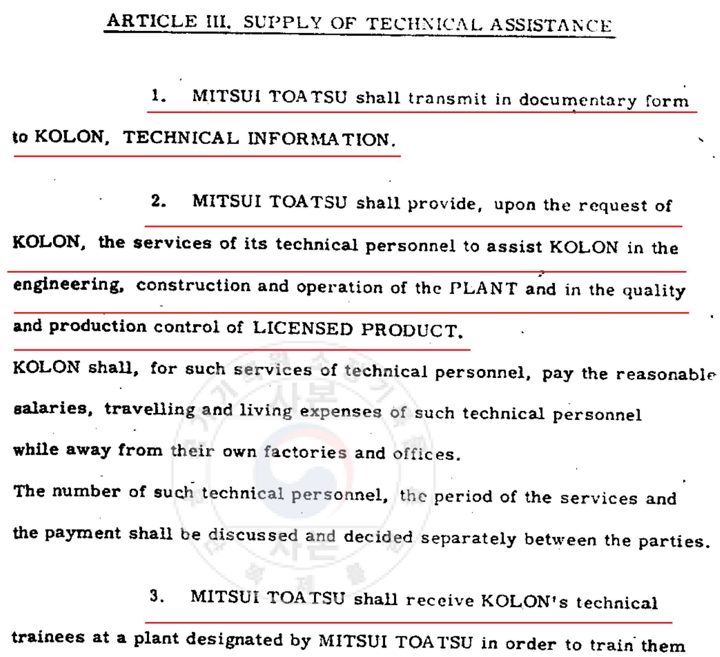
ONLINE APPENDIX

A. Data

Firm-level data. From the contract documents, we obtain three main pieces of information: the names of domestic firms, the names of foreign firms, and the calendar years in which the contracts were made. The balance sheet data includes firms with more than 50 employees. In cases where a firm merged with another, we treated the acquired firm as an exit. For firms with missing sales, we impute sales using asset information. The production locations' addresses are converted to the 2010 administrative divisions of South Korea. Regions are aggregated upto 86 regions based on their electoral districts. Firms are categorized into 10 sectors, four of which are classified as heavy manufacturing, as shown in Table A1. The numbers inside the parenthesis are ISIC Revision 3.1 codes.

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



ARTICLE III. SUPPLY OF TECHNICAL ASSISTANCE

1. MITSUI TOATSU shall transmit in documentary form to KOLON, TECHNICAL INFORMATION.

2. MITSUI TOATSU shall provide, upon the request of KOLON, the services of its technical personnel to assist KOLON in the engineering, construction and operation of the PLANT and in the quality and production control of LICENSED PRODUCT.
KOLON shall, for such services of technical personnel, pay the reasonable salaries, travelling and living expenses of such technical personnel while away from their own factories and offices.
The number of such technical personnel, the period of the services and the payment shall be discussed and decided separately between the parties.

3. MITSUI TOATSU shall receive KOLON's technical trainees at a plant designated by MITSUI TOATSU in order to train them

Other regional and sectoral data. The regional population data are sourced 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 calculate averages across four-digit ISIC codes. For years with missing data, we impute values using the geometric average. We obtain input-output tables from the Bank of Korea and align the codes in the input-output tables with the ISIC codes.

Table A1: Sector Classification

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

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

Table A2: Number of Firms across Sectors by the Top 15 Business Groups

	Ranking	Number of firms across sectors										
	(total assets)	All	Chemicals	Electronics	Metals	Transport. equip.	Food	Textile	N.e.c.	Wood	Pharma.	Nonmetallic mineral
Top 15 business groups	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hyundai	1	13	1	1	3	4	0	0	0	1	0	3
Samsung	2	14	2	6	1	1	1	1	0	2	0	0
Lucky	3	12	2	9	1	0	0	0	0	0	0	0
Daewoo	4	14	2	1	2	3	1	4	1	0	0	0
Hyosung	5	14	5	1	0	2	0	5	0	1	0	0
Ssangyong	6	4	1	1	0	1	0	0	0	0	0	1
Hanil Synthetic Fiber	7	2	1	0	0	0	0	1	0	0	0	0
Gukje	8	9	1	0	3	1	0	3	0	1	0	0
Taihan Electric Wire	9	7	0	5	0	1	1	0	0	0	0	0
Sammi	10	5	0	0	4	0	0	0	0	0	0	1
Kia	11	8	0	0	1	7	0	0	0	0	0	0
Hanwha	12	9	4	1	1	1	1	0	0	0	0	1
Choongbang	13	3	0	0	0	0	0	3	0	0	0	0
Hanguk silk	14	13	2	2	0	1	0	6	1	1	0	0
Kumho	15	8	4	2	1	0	0	1	0	0	0	0

Notes. This table reports the number of firms across different sectors by the top 15 business groups.

B. Empirics

B.1 An Example of POSCO

We provide an example of POSCO to illustrate how technology adoption benefited firms through three channels documented by our empirical analysis. POSCO, now one of the top five steel producers globally, was the first integrated steel mill in South Korea. Integrated steel mills are vital for industrialization, producing high-quality steel used as inputs for various manufacturing sectors.

In 1968, POSCO signed its first technology adoption contract with Japan's Nippon Steel Corporation (NSC). This contract involved the transfer of blueprints and the training by NSC's engineers for POSCO's engineers. The contract was profitable for NSC, as the fee paid by POSCO amounted to 20% of NSC's annual exports in plant engineering. The Korean government also supported POSCO by subsidizing the costs of capital equipment via guaranteed foreign credit. As a result, POSCO began production in 1973, exemplifying the first finding on the direct effects of adopters.

Moreover, local labor mobility enabled knowledge transfer beyond POSCO. Engineers trained at POSCO gained expertise through learning by doing and reverse engineering. Many later moved to smaller local mills or capital goods producers, spreading their newly acquired knowledge and enhancing the performance of these local firms. From this knowledge, these local firms began producing more sophisticated equipment—such as water treatment systems, dust collection devices, and large magnetic cranes—that had previously been imported during the early 1970s before the implementation of the HCI Drive (Enos and Park, 1988, p. 210-211). This diffusion of knowledge via labor mobility aligns with our second finding on local spillovers.

Furthermore, this diffusion facilitated POSCO's adoption at a later stage. In 1980, POSCO planned to adopt new computerization technology, which required significant capital investment for equipment and plant expansion. Despite no longer receiving government credit, POSCO moved forward with adoption, as the availability of cheaper domestically produced capital inputs—manufactured by local firms—helped reduce setup costs (POSCO, 2018, p.138-141). By 1980, locally produced equipment accounted for 35% of total expenditures on expansion, compared to just 12% during the first adoption in 1968. This underscores the role of local firms in reducing adoption costs, consistent with our third finding and the theoretical model's focus on fixed adoption costs.

B.2 Construction of Controls for Business Group Sales Shares for the Regressions for Local Spillovers and Complementarity

Business group sales shares. We define a variable, $\text{Share}^{\text{sale}}_{(-i)nj,t-h}$, analogous to the adopter shares in equation (3.4) and include it as controls in equation (3.5) in a reduced-form fashion, with the corresponding IV discussed below. $\text{Share}^{\text{sale}}_{(-i)nj,t-h}$ is the region-sector level share of sum of sales by business group to total region-sector sales:

$$\text{Share}^{\text{sale}}_{(-i)nj,t-h} = \frac{\sum_{\tilde{g}\neq g(i)} \text{Sale}_{(-i)\tilde{g}nj,t-h}}{\text{Sale}_{(-i)nj,t-h}}. \tag{B.1}$$

$\text{Sale}_{(-i)\tilde{g}nj,t-h}$ is total sales of firms affiliated business group $\tilde{g}$, excluding firm i, in region-sector nj in period $t-h$, and $\text{Sale}_{(-i)nj,t-h}$ is total sales of firms in region-sector nj in $t-h$, excluding i.

IV. Analogous to the IV for adopter shares in equation (3.6), we define the following IV for business group sales shares:

$$Z^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h} = \sum_{\tilde{g}\neq g(i)} D_{\tilde{g}njt_0} \times \frac{\text{Sale}^{\geq 100\text{km},t_0}_{\tilde{g}(-n)j,t-h}}{\widetilde{\text{Sale}}^{\text{p}}_{(-i)nj,t-h}},$$

where $D_{\tilde{g}njt_0}$ is a dummy indicating whether business group $\tilde{g}$ has at least one firm in region-sector nj in the initial year t_0. $\text{Sale}^{\geq 100\text{km},t_0}_{\tilde{g}(-n)j,t-h}$ is total sum of sales of sector j firms in year $t-h$ that were affiliated with business group $\tilde{g}$ and started operating before the initial year t_0, excluding firms located in region n and within a 100 km radius of region n. When summing over these business groups, we exclude business group $g(i)$ with which firm i is affiliated. $\widetilde{\text{Sale}}^{\text{p}}_{(-i)nj,t-h}$ is the predicted sales of firms in nj in year $t-h$, excluding i, constructed using the national-level growth and initial sales of local firms. Specifically,

$$\widetilde{\text{Sale}}^{\text{p}}_{(-i)nj,t-h} \equiv g^{\text{sale}}_{(-n)j} \times \text{Sale}_{(-i)nj,t_0-h},$$

where $g^{\text{sale}}_{(-n)j}$ is the national-level growth of sector j's total sales, excluding firms in region n, and $\text{Sale}_{(-i)nj,t_0-h}$ is region-sector nj's initial total sales, excluding firm i, in year t_0-h.

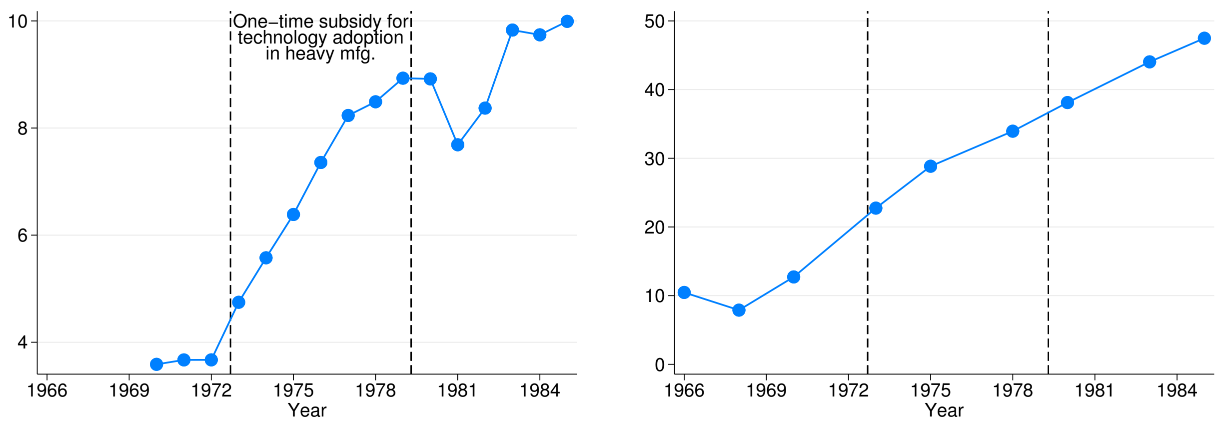
The IV is constructed by taking the long-differences of $Z^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h}$:

$$\text{IV}^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h} = \Delta Z^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h}. \tag{B.2}$$

It is important to note that $\text{IV}^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h}$ and $\text{IV}^{\geq 100\text{km},t_0}_{inj,t-h}$ exploit different types of variation. $\text{IV}^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h}$ exploits business groups' sales expansion outside of the focal region, while $\text{IV}^{\geq 100\text{km},t_0}_{inj,t-h}$ captures business groups' technology adoption activities outside of the focal region. Also note that both $\text{IV}^{\text{sale, }\geq 100\text{km},t_0}_{inj,t-h}$ and $\text{IV}^{\geq 100\text{km},t_0}_{inj,t-h}$ are computed based on *pre-existing* firms located outside of a 100 km radius from the focal region.

B.3 Additional Figures and Tables

Figure B1: Big Push and Industrialization in South Korea. Heavy Manufacturing Employment and Export Shares

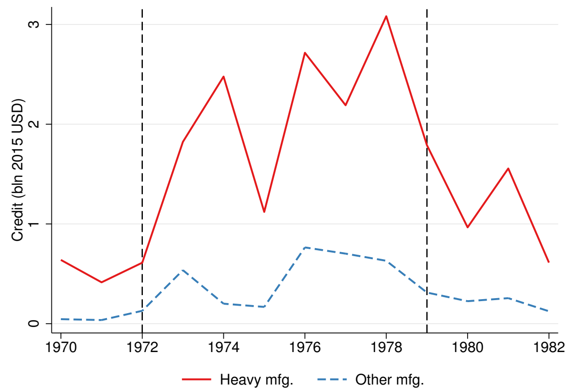


A. Heavy mfg. share of employment (%)

B. Heavy mfg. share of exports (%)

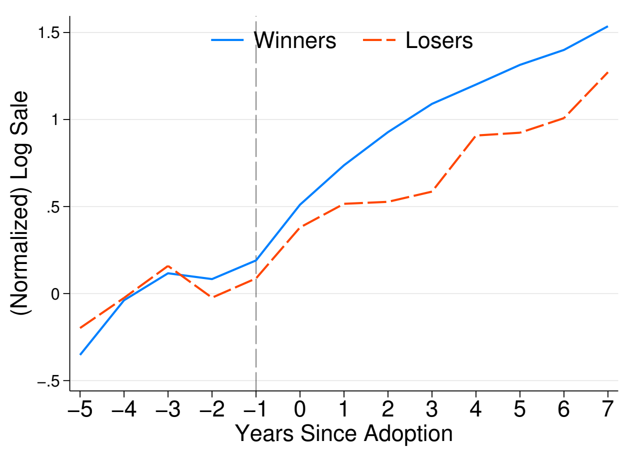
Notes. The two dotted vertical lines indicate the start and end of the South Korean government's big push, which temporarily subsidized adoption of modern technologies from foreign firms in heavy manufacturing sectors from 1973 to 1979. Panels A and B illustrate heavy manufacturing sectors' employment shares to total employment and its export shares to total exports, respectively. We obtain sectoral employment data from the KLEMS for the post-1970 period (pre-1970 data is unavailable), and exports from the Bank of Korea's input-output tables.

Figure B2: Supporting Evidence for the Temporary Nature of the Policy. Allocation of Directed Credit



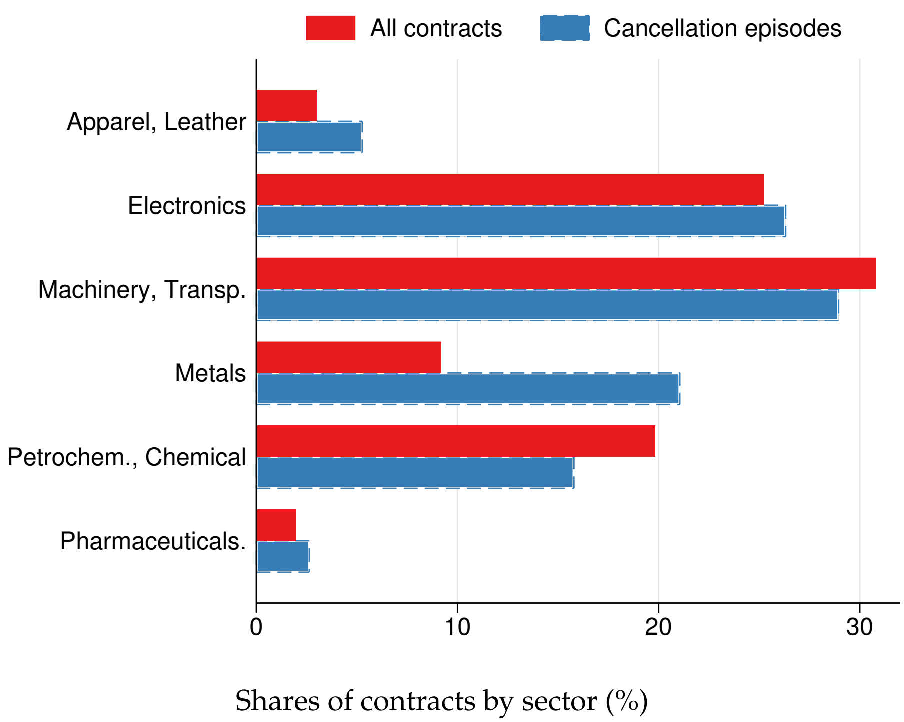
Notes. The figure provides supporting evidence of the temporary nature of the policy. The red solid and blue long-dashed lines represent the sum of foreign credit (in 2015 million USD) allocated to heavy manufacturing firms and non-heavy manufacturing firms, respectively. The vertical lines indicate the years 1973 and 1979, marking the start and end of the HCI Drive, respectively. The data, sourced from Choi and Levchenko (2024), shows that the sum of foreign credit—the main subsidy instrument—allocated to heavy manufacturing firms surged sharply in 1973 before returning to its original level after 1979. In contrast, credit for other sectors did not experience such a surge between 1973 and 1979.

Figure B3: Raw Plot of the Log Sales of the Winners vs. Losers Sample



Notes. The figure displays the mean of log sales for winners and losers (blue solid and red dashed lines), normalized by the average before the event.

Figure B4: Distributions of Contracts by Sectors



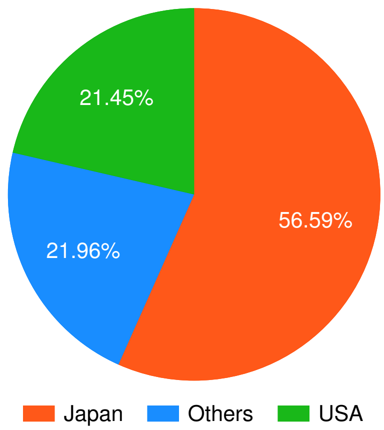
Notes. The figure presents the sectoral distribution of all contracts ($N = 1,634$) and cancellation episodes ($N = 38$).

Table B1: Descriptive Statistics: Winners vs. Losers Design Samples from the Year of the Cancellation to 5 Years before the Cancellation

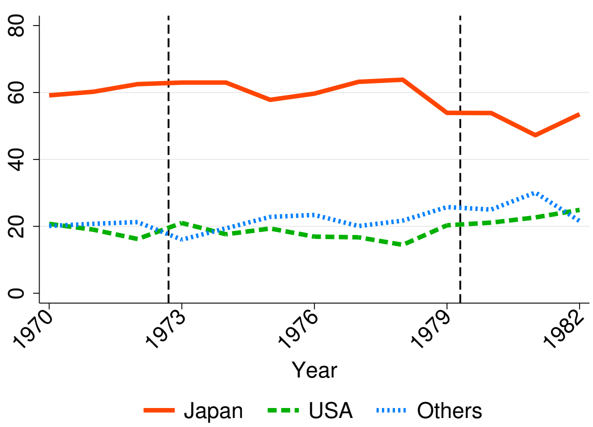
	Winner				Loser				(Col. 1 - Col. 5)	
	Mean	Med.	SD	Obs.	Mean	Med.	SD	Obs.	t-stat.	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Winners vs. losers balance										
Log sales	17.58	17.47	1.94	447	17.97	18.01	1.86	180	1.23	[0.27]
Log emp.	7.02	7.13	1.28	329	7.09	7.25	1.53	144	0.04	[0.83]
Log fixed assets	16.75	16.72	2.16	447	17.08	17.48	2.22	180	0.52	[0.48]
Log assets	17.78	17.63	1.97	447	18.02	18.17	1.99	180	0.33	[0.57]
$\mathbb{1}[\text{Subsidy}_{it}]$	0.11	0	0.32	447	0.13	0	0.33	180	0.05	[0.98]
$\mathbb{1}[\text{Export promo.}_{it}]$	0.12	0	0.33	447	0.12	0	0.33	180	0	[0.98]
Business group status	0.43	0	0.50	447	0.47	0	0.50	180	0.11	[0.74]
Panel B. Winners vs. losers. Foreign firm patent activity balance										
Ihs # cum. patents	1.79	0	2.65	90	1.62	0	2.67	38	0.13	[0.72]
Ihs # cum. citations	1.94	0	2.89	90	1.80	0	2.91	38	0.07	[0.79]
$\mathbb{1}[\text{\# cum. patents} \geq 0]$	0.36	0	0.48	90	0.32	0	0.47	38	0.18	[0.67]
$\mathbb{1}[\text{\# cum. citations} \geq 0]$	0.36	0	0.48	90	0.34	0	0.48	38	0.02	[0.89]
Panel C. All adopters in the same region-sector-period vs. losers balance										
Log sales	17.40	17.16	1.87	540	17.97	18.01	1.86	180	2.55	[0.12]
Log emp.	6.76	6.86	1.36	396	7.09	7.25	1.53	144	0.94	[0.34]
Log fixed assets	16.54	16.24	2.10	540	17.08	17.48	2.22	180	1.35	[0.25]
Log assets	17.55	17.39	1.93	540	18.02	18.17	1.99	180	1.23	[0.28]
$\mathbb{1}[\text{Subsidy}_{it}]$	0.10	0	0.30	540	0.13	0	0.33	180	0.16	[0.69]
$\mathbb{1}[\text{Export promo.}_{it}]$	0.10	0	0.31	540	0.12	0	0.33	180	0.17	[0.68]
Business group status	0.39	0	0.49	540	0.47	0	0.50	180	0.40	[0.53]

Notes. Panel A reports descriptive statistics of the winners vs. losers design samples from 5 years before the cancellations to the year of the cancellation. Panel B reports descriptive statistics of patent activities by foreign firms matched with winners and losers. We report inverse hyperbolic sine transformation and dummies of cumulative numbers of patents and citations. Panel C reports descriptive statistics of all adopters in the same region-sectors as losers, who adopted technologies at the time when losers made contracts. In the second rows of Panels A and C, the sample size decreases due to missing employment data. Column 9 reports the t-statistics of mean differences between winners and losers with their p-values in brackets in column 10. All monetary values are converted into 2015 US dollars.

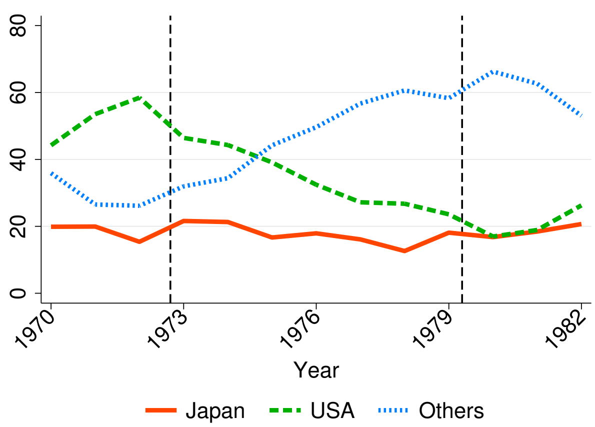
Figure B5: Technology Adoption, Export, and Import Shares by Country



A. Technology adoption



B. Export



C. Import

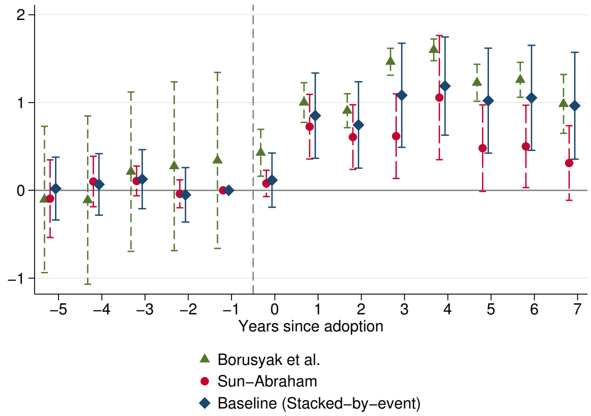
Notes. This figure depicts the shares of technology adoption, export, and import in the heavy manufacturing sectors across countries. The technology adoption shares represent the number of contracts from each country divided by the total number of contracts.

Table B2: Robustness. Covariate Balance Test

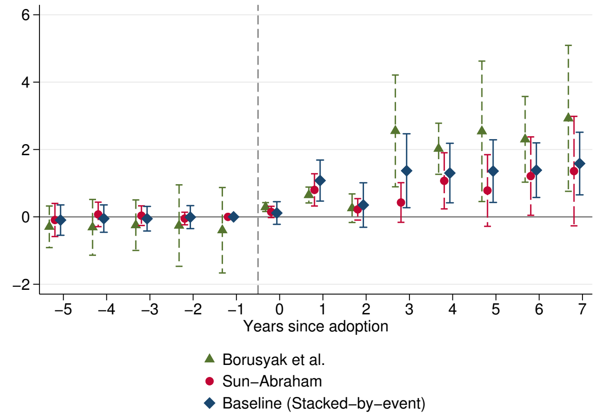
Dep.	$\mathbb{1}[\text{Winner}_{it}]$															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ln Sale_{it}	−0.02							−0.10*	−0.03							−0.12*
	(0.02)							(0.05)	(0.04)							(0.07)
ln Employment_{it}		−0.01						−0.01		0.01						−0.00
		(0.04)						(0.06)		(0.05)						(0.06)
ln Fixed asset_{it}			−0.01					−0.14**			−0.01					−0.10
			(0.02)					(0.06)			(0.04)					(0.07)
ln Asset_{it}				−0.01				0.23**				−0.00				0.22*
				(0.02)				(0.09)				(0.04)				(0.12)
$\mathbb{1}[\text{Subsidy}_{it}]$					−0.03			−0.05					0.03			−0.00
					(0.14)			(0.13)					(0.18)			(0.12)
$\mathbb{1}[\text{Export promo}_{it}]$						−0.00		0.05						0.01		0.01
						(0.09)		(0.10)						(0.10)		(0.10)
$\mathbb{1}[\text{Chaebol}_{it}]$							−0.04	0.03							−0.04	0.06
							(0.11)	(0.11)							(0.14)	(0.14)
Joint F p-val.								[0.30]								[0.68]
N	627	473	627	627	627	627	627	473	627	472	627	627	627	627	627	472
Match FE									✓	✓	✓	✓	✓	✓	✓	✓

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 5 years before the cancellation to the year of the cancellation. The dependent variables are dummies of being winners. The regressors are log sales, log employment, log fixed assets, log assets, dummies of receiving subsidies, dummies of receiving export promotion, and dummies of being affiliated with business groups. For the joint specification in columns 8 and 16, we report p-values of F-statistics in brackets that test a hypothesis that the observables are jointly zero. Columns 9-16 include match fixed effects. In columns 2, 8, 10, and 16, the sample size decreases due to missing employment data.

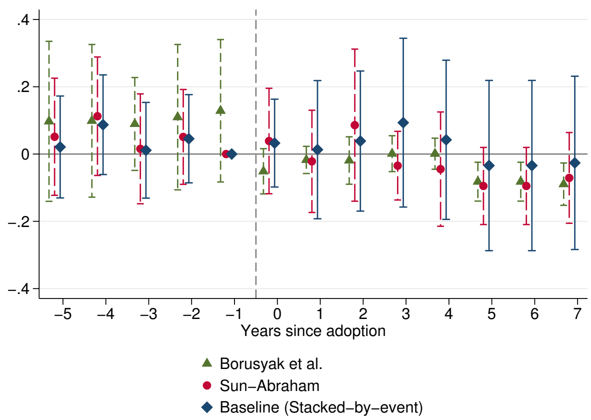
Figure B6: Robustness. Alternative Estimators. Event Study. Direct Effects on Adopters. Winners vs. Losers Design



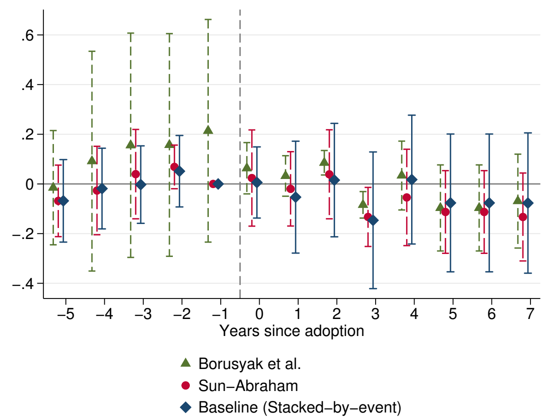
A. Log sale



B. TFPR



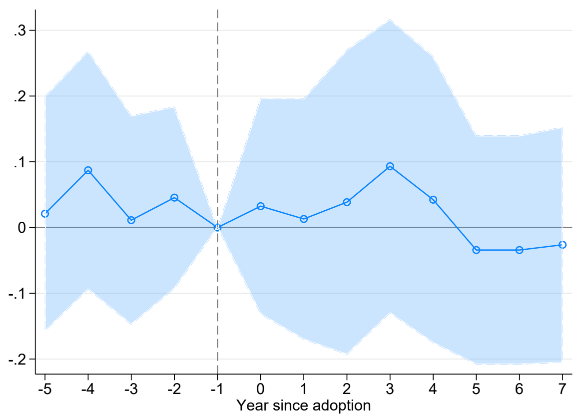
C. $\mathbb{1}[\text{Subsidy}_{it} > 0]$

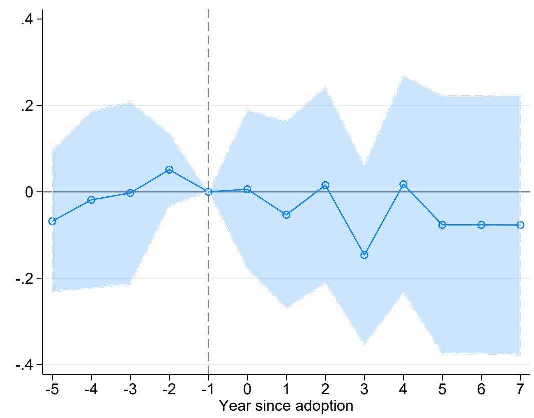


D. $\mathbb{1}[\text{Export promo.}_{it} > 0]$

Notes. This figure presents the estimated β_τ in equation (3.1) based on the winners vs. losers research design from the baseline and estimators developed by Sun and Abraham (2021) and Borusyak et al. (forthcoming). In Panels A, B, C, and D, the dependent variables are log sales, log revenue TFP, dummies of receiving directed credit, and dummies of receiving export promotion, respectively. The vertical lines represent the 95% confidence intervals based on standard errors two-way clustered at the match and firm levels for the baseline and Sun and Abraham (2021) estimators and those clustered at the match level for the Borusyak et al. (forthcoming) estimators. β_{-1} is normalized to zero. All specifications include match-year and match-firm fixed effects.

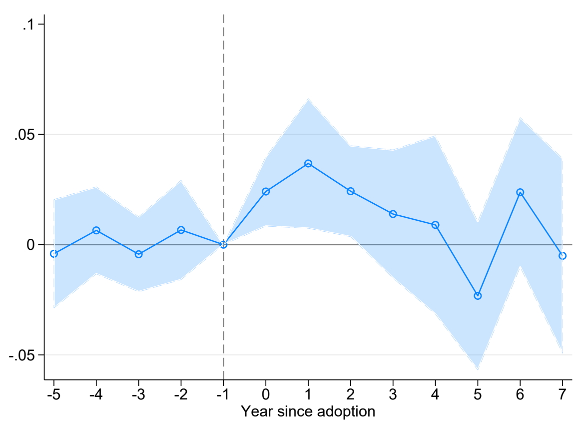
Table B3: Subsidies and Export Promotion. Comparison between TWFE Event Study and Winners vs. Losers Design. Direct Effects on Adopters

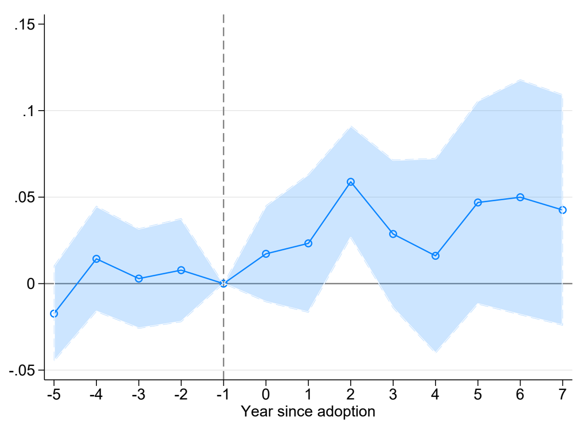




Winners vs. losers research design

A. $\mathbb{1}[\text{Subsidy}_{it} > 0]$ B. $\mathbb{1}[\text{Export promo.}_{it} > 0]$





Full TWFE

C. $\mathbb{1}[\text{Subsidy}_{it}]$ D. $\mathbb{1}[\text{Export promo.}_{it}]$

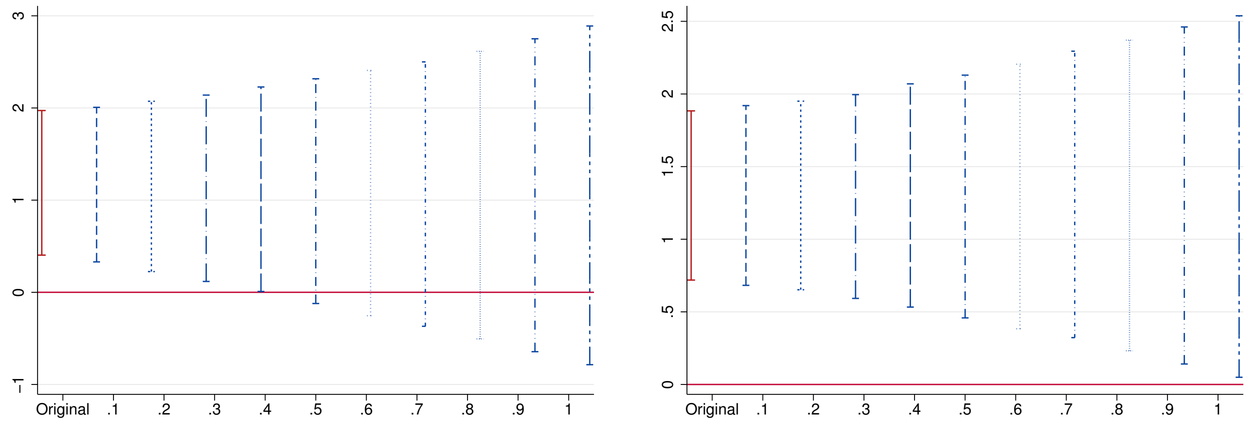
Notes. This figure presents the estimated β_τ from the winners vs. losers research design (equation (3.1)) in Panels A and B and those from the full TWFE event study (equation (3.3)) in Panels C and D. The 95% confidence intervals are based on standard errors two-way clustered at the match and firm levels in Panels A and B and clustered at the regional level in Panels C and D. The dependent variables are dummies of receiving directed credit (subsidy) in Panels A and C and export promotion in Panels B and D. β_{-1} is normalized to zero. Specifications include match-year and match-firm fixed effects in Panels A and B, and include firm and region-sector-time fixed effects in Panels C and D.

Table B4: Robustness. Alternative Inference and Levels of Clustering. Pooled Diff-in-diff. Direct Effects on Adopters. Winners vs. Losers Design

Dep.	Sale	TFPR	Subsidy	Export promo.
	(1)	(2)	(3)	(4)
Coefficient $\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]$	0.91	0.94	−0.01	−0.05
Alternative inference				
Baseline	[< 0.01]	[< 0.01]	[0.82]	[0.62]
Randomization inference (Young, 2019)	[< 0.01]	[< 0.01]	[0.82]	[0.62]
Wild bootstrap (Cameron et al., 2008)	[< 0.01]	[< 0.01]	[0.91]	[0.68]
Wild bootstrap (MacKinnon et al., 2023)	[< 0.01]	[< 0.01]	[0.91]	[0.67]
# Clusters	38×106	35×98	38×106	38×106
Alternative levels of clustering				
Match-level	[< 0.01]	[< 0.01]	[0.82]	[0.62]
# Clusters	38	35	38	38
Firm-level	[< 0.01]	[< 0.01]	[0.82]	[0.66]
# Clusters	106	98	106	106
N	852	537	852	852
Fixed effects	Match×Firm, Match×Year			

Notes. This table reports p-values, corresponding to the null that the estimated coefficient of $\mathbb{1}[\text{Winner}_{it}] \times \mathbb{1}[\text{Post}_{mt}]$ of the pooled diff-in-diff specification in equation (3.2) is equal to zero, from alternative inference procedures. In columns 1-4, the dependent variables are log sales, revenue TFP, dummies of receiving directed credit, and dummies of participating in trade fairs. In column 2, the sample size decreases due to missing employment data. P-values based on standard errors two-way clustered at the match and firm-levels are reported in brackets, obtained from the baseline asymptotic inference, randomization inference (Young, 2019), wild bootstrap (Cameron et al., 2008), and wild bootstrap that jackknifes the bootstrapped data (MacKinnon et al., 2023), and alternative clustering at the match and firm-levels. All specifications include match-year and match-firm fixed effects.

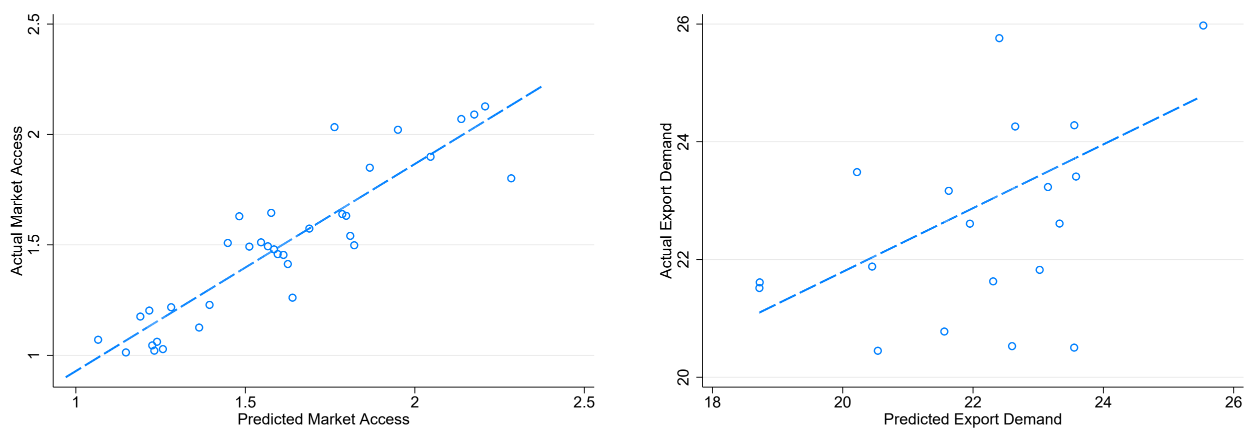
Figure B7: Robustness. Sensitivity to Violations of the Parallel Trend Assumption. Direct Effects on Adopters. Winners vs. Losers Design



A. Log sale B. TFPR

Notes. This figure presents results of the sensitivity checks for potential violations of the parallel trend assumption based on Rambachan and Roth (2023). The figure reports the estimated 90% confidence intervals, based on standard errors two-way clustered at the firm and match levels, for β_4 of equation (3.1) over different values of M which is a parameter that governs magnitude of violations to the parallel trend assumption: $\Delta^{RM}(M) = \{\delta : \forall t \geq 0, |\delta_{t+1} - \delta_t| \leq M \times \max_{s \leq 0} |\delta_{s+1} - \delta_s|$, where $\max_{s \leq 0} |\delta_{s+1} - \delta_s|$ is the maximum pre-treatment violation of parallel trends. $M = 1$ is a natural benchmark, which bounds the worst-case post-treatment difference in trends by the maximum in pre-treatment periods (Rambachan and Roth, 2023, p.2563). β_{-1} is normalized to zero. In Panels A and B, the dependent variables are log sales and revenue TFP, respectively. All specifications include match-year and match-firm fixed effects.

Figure B8: Correlations between Market Access Measures based on Actual and Predicted Values



A. Market access B. Export demand

Notes. Each circle is the mean changes in actual and predicted market access (equation (3.7)) or export demand (the log distance to port interacted with predicted sectoral exports) within bins optimally selected following Cattaneo et al. (2024). The x-axis shows values based on actual sales or exports, while the y-axis displays the corresponding predicted values.

Table B5: Robustness. Alternative Outcomes and Estimation Samples. Direct Effects on Adopters

Robustness	Alternative outcomes				Alternative samples				
Dep.	Labor prod.	TFPR^{OP}	Fixed asset	Export dum.	Sale				
Sample.	Baseline				Non-missing emp.	# match = 2	# match = 3	# match = 5	All adopters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
5 years before	−0.26	−0.13	−0.04	0.22	0.00	−0.10	−0.03	0.02	0.02
	(0.64)	(0.48)	(0.26)	(0.14)	(0.24)	(0.24)	(0.21)	(0.21)	(0.21)
4 years before	−0.12	−0.08	−0.01	0.07	−0.02	0.02	0.05	0.07	0.07
	(0.50)	(0.37)	(0.21)	(0.12)	(0.22)	(0.17)	(0.15)	(0.15)	(0.15)
3 years before	−0.25	−0.11	−0.03	−0.06	0.03	0.08	0.11	0.13	0.15
	(0.38)	(0.28)	(0.16)	(0.13)	(0.14)	(0.13)	(0.11)	(0.11)	(0.12)
2 years before	−0.14	−0.05	0.15	0.04	0.02	−0.06	−0.04	−0.05	−0.03
	(0.19)	(0.16)	(0.18)	(0.09)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
1 year before									
Year of event	0.19	0.17	−0.06	0.04	0.08	0.16	0.12	0.11	0.15^{*}
	(0.17)	(0.15)	(0.09)	(0.07)	(0.12)	(0.10)	(0.09)	(0.09)	(0.09)
1 year after	1.37^{**}	1.12^{**}	0.37^{*}	0.16	1.16^{***}	0.71^{***}	0.84^{***}	0.86^{***}	0.88^{***}
	(0.67)	(0.54)	(0.22)	(0.19)	(0.42)	(0.21)	(0.28)	(0.27)	(0.27)
2 years after	0.53	0.27	0.29	0.41^{**}	0.45	0.62^{***}	0.74^{***}	0.77^{***}	0.78^{***}
	(0.47)	(0.38)	(0.18)	(0.20)	(0.27)	(0.20)	(0.26)	(0.24)	(0.24)
3 years after	1.14^{***}	1.21^{***}	0.32	0.03	1.39^{***}	0.90^{***}	1.08^{***}	1.09^{***}	1.10^{***}
	(0.33)	(0.26)	(0.32)	(0.29)	(0.15)	(0.28)	(0.39)	(0.39)	(0.39)
4 years after	0.61	0.92^{*}	0.64	−0.17	1.47^{***}	0.99^{**}	1.18^{**}	1.19^{**}	1.21^{**}
	(0.73)	(0.53)	(0.50)	(0.22)	(0.14)	(0.44)	(0.48)	(0.48)	(0.48)
5 years after	2.22^{***}	1.44^{***}	0.50	−0.17	1.25^{***}	0.95^{**}	1.01^{**}	1.03^{**}	1.04^{**}
	(0.44)	(0.37)	(0.54)	(0.19)	(0.23)	(0.43)	(0.43)	(0.43)	(0.43)
6 years after	1.46^{***}	1.25^{***}	0.53	−0.06	1.68^{***}	0.98^{**}	1.05^{**}	1.06^{**}	1.07^{**}
	(0.45)	(0.34)	(0.51)	(0.28)	(0.39)	(0.40)	(0.41)	(0.41)	(0.41)
7 years after	0.88	1.48^{**}	0.11	−0.09	1.91^{***}	1.03^{***}	0.96^{***}	0.97^{***}	0.98^{***}
	(1.13)	(0.56)	(0.29)	(0.24)	(0.38)	(0.35)	(0.35)	(0.34)	(0.34)
# Clusters	98 × 35	98 × 35	106 × 38	106 × 38	98 × 35	88 × 38	99 × 38	112 × 38	122 × 38
N	537	537	844	852	537	688	777	903	975
Fixed effect	Match×Year, Match×Firm								

Notes. Standard errors in parenthesis are two-way clustered at the firm and match levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 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. In columns 1, 2, 3, 4, and 5-9, the dependent variables are log labor productivity, revenue TFP based on Olley and Pakes (1996), log fixed asset, dummies of exporting, and log sales, respectively. In columns 1-2, the sample size decreases due to missing employment data. In column 5, we consider estimation sample with non-missing employment information. In columns 6, 7, and 8, we consider alternative numbers of matched winners of 2, 3, and 5, respectively. In column 9, we construct a set of winners using all firms that adopted technologies in the year of the event within the corresponding losers' region-sectors. All specifications include match-firm and match-year fixed effects.

Table B6: First Stage Regression. Local Spillovers and Complementarity

	Local spillovers						Local complementarity		
Second stage dep.	$\Delta \ln \text{Sale}_{it}$			ΔTFPR_{it}			$\Delta\mathbb{1}[\text{New Contract}_{it}]$		
First stage dep.	$\Delta\text{Share}_{(-i)nj,t-2}$ 1972-1979 or 1973-1980								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{IV}^{\geq 100\text{km},t_0}_{(-i)nj,t-2}$	0.19***	0.19***	0.19***	0.17***	0.17***	0.18***	0.19***	0.19***	0.19***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
# clusters	79 × 1,294			67 × 742			86 × 1,548		
N	1,492	1,492	1,492	824	824	824	1,977	1,977	1,977
Fixed effects	Region, Sector, Group×Sector								
Business group sales share		✓	✓		✓	✓		✓	✓
Additional ctrl			✓			✓			✓

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 3 and 4, respectively. Adopter shares and IV are defined in equations (3.4) and (3.6), respectively. In columns 1-6, the sample consists of firms that never adopted technology during the sample period, while in columns 7-9, the sample consists of all firms. In columns 4-6, the sample size decreases due to missing employment data. Columns 3. 6, and 9 include the vector of additional controls used in column 8 of Tables 3-4. All specifications include the initial dependent variables, the predicted business groups' sales shares within region sectors (equation (B.2), detailed in Appendix B.2), and region, sector, and sector-group fixed effects.

Table B7: Robustness. Alternative Specification with the Two Endogenous Variables. Local Spillovers and Complementarity

Dep.	1972-1979 or 1973-1980					
	$\Delta \ln \text{Sale}_{it}$		ΔTFPR_{it}		$\Delta\mathbb{1}[\text{New Contract}_{it} > 0]$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\text{Share}_{(-i)nj,t-2}$	4.06***	3.72***	2.47***	2.45***	0.76**	0.78**
	(1.16)	(1.08)	(0.89)	(0.86)	(0.33)	(0.33)
$\Delta\text{Share}^{\text{sale}}_{(-i)nj,t-2}$	1.33**	0.93	0.73**	0.73**	−0.15	−0.15
	(0.64)	(0.67)	(0.34)	(0.35)	(0.27)	(0.24)
KP-F	5.77	6.46	7.26	7.07	7.54	10.29
SW-F, $\text{IV}^{\geq 100\text{km},t_0}_{(-i)nj,t-2}$	11.30	12.34	12.25	12.47	10.83	9.51
SW-F, $\text{IV}^{\text{sale},\geq 100\text{km},t_0}_{(-i)nj,t-2}$	12.28	15.21	17.32	19.23	15.44	21.79
# Clusters	$79 \times 1{,}294$		67×742		$86 \times 1{,}548$	
N	1,492	1,492	824	824	1,977	1,977
Fixed effects	Region, Sector, Sector × Group					
Additional ctrl		✓		✓		✓

Notes. Standard errors two-way clustered at the region and business group levels are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $\text{Share}^{\text{sale}}_{(-i)nj,t-2}$ is business groups' sales shares within region-sectors, excluding own group, defined in equation (B.1), instrumented by the corresponding IV (equation (B.2), detailed in Appendix B.2). In columns 1-2, 3-4, and 5-6, the dependent variables are changes in log sales, revenue TFP, and dummies of making new adoption contracts between 1972-1979 or 1973-1980, respectively. In columns 1-4, the sample consists of firms that never adopted technology during the sample period, while in columns 5-6, the sample consists of all firms. In columns 3-4, the sample size decreases due to missing employment data. KP-F and SW-F are the Kleibergen-Paap and Sanderson-Windmeijer F-statistics. Columns 2, 4, and 6 include the vector of additional controls used in column 8 of Tables 3-4. All specifications include the initial dependent variables and region, sector, and sector-group fixed effects.

Table B8: Robustness. Alternative Cutoff. Heterogeneous Effects of Local Complementarity in Technology Adoption Decisions

Dep.	Δ[New Contract$_{it}$] 1972-1979 or 1973-1980			
Cutoff percentile of MA	70th (1)	75th (2)	80th (3)	85th (4)
Low MA $\times$ ΔShare$_{(-i)nj,t-2}$	-2.83	0.24	0.29*	0.21
	(2.07)	(0.18)	(0.17)	(0.15)
High MA $\times$ ΔShare$_{(-i)nj,t-2}$	0.89**	1.06*	1.07*	1.10*
	(0.38)	(0.55)	(0.56)	(0.59)
KP-F	1.98	19.60	21.11	17.34
SW-F, Low MA	4.08	339.23	455.35	338.68
SW-F, High MA	23.20	43.90	47.88	44.98
p-val. (low MA = High MA)	[0.08]	[0.08]	[< 0.10]	[0.12]
# Clusters	86 × 1,548	86 × 1,548	86 × 1,548	86 × 1,548
N	1,977	1,977	1,977	1,977
Fixed effect	Region, Sector, Group×Sector			
Business group sales share	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓

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 (3.5). Adopter shares Share$_{(-i)nj,t-h}$ and the IV are defined in equations (3.4) and (3.6). Columns 1-4 include interaction terms between adopter shares and dummies for low and high initial market access, defined based on the 70th, 75th, 80th, and 85th percentiles, respectively. The dependent variables are changes of dummies of making new adoption contracts between 1972-1979 or 1973-1980. All specifications include the predicted business groups' sales shares (equation (B.2), detailed in Appendix B.2), the vector of additional controls used in column 8 of Table 4, and region, sector, and sector-group fixed effects, and the initial levels of dependent variables. KP-F and SW-F are the Kleibergen-Paap and Sanderson-Windmeijer F-statistics, respectively. We also report the p-values in brackets associated with the null that the coefficients of the two interaction terms are equal.

Table B9: Robustness. Alternative IVs. Local Spillovers and Complementarity

Robustness	Excl. business groups whose total fixed assets exceed certain thresholds			Excl. Samsung Hyundai	Alternative distance			
	30%	50%	70%		50 km	75 km	125 km	150 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Dep. $\Delta \ln Sale_{it}$ *1972-1979 or 1973-1980*							
$\Delta\text{Share}_{(-i)nj,t-2}$	2.50***	2.79***	2.77***	2.80***	2.70***	2.79***	2.69***	2.68***
	(0.77)	(0.87)	(0.87)	(0.88)	(0.87)	(0.86)	(0.82)	(0.83)
KP-F	15.93	18.15	18.09	18.30	18.20	17.44	16.58	16.35
# Clusters	$79 \times 1{,}294$							
N	1,492	1,492	1,492	1,492	1,492	1,492	1,492	1,492
	Panel B. Dep. $\Delta TFPR_{it}$ *1972-1979 or 1973-1980*							
$\Delta\text{Share}_{(-i)nj,t-2}$	1.55***	1.64***	1.63***	1.60***	1.53***	1.56***	1.54***	1.53***
	(0.53)	(0.57)	(0.57)	(0.59)	(0.56)	(0.56)	(0.54)	(0.55)
KP-F	19.69	22.38	22.30	21.32	20.79	20.08	19.26	18.94
# Clusters	67×742							
N	824	824	824	824	824	824	824	824
	Panel C. Dep. $\Delta \mathbb{1}[New\ Contract_{it} > 0]$ *1972-1979 or 1973-1980*							
$\Delta\text{Share}_{(-i)nj,t-2}$	0.99**	1.05*	1.04*	0.86**	0.80**	0.86**	0.80*	0.80*
	(0.49)	(0.53)	(0.53)	(0.42)	(0.40)	(0.42)	(0.40)	(0.40)
KP-F	12.97	15.03	15.00	18.87	21.49	19.20	15.93	15.92
# Clusters	$86 \times 1{,}548$							
N	1,977	1,977	1,977	1,977	1,977	1,977	1,977	1,977
Fixed effect	Region, Sector, Group×Sector							
Business group sales share	✓	✓	✓	✓	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓	✓	✓	✓	✓

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 IV estimates of equation (3.5). Adopter shares and IV are defined in equations (3.4) and (3.6). In Panels A, B, and C, the dependent variables are changes in log sales, log revenue TFP, and dummies of making new adoption contracts between 1972-1979 or 1973-1980, respectively. In Panels A and B, the sample consists of firms that never adopted technology during the sample period, while in Panel C, the sample consists of all firms. In Panel B, the sample size decreases due to missing employment data. All specifications include business groups' predicted sales shares within region-sectors (equation (B.2), detailed in Appendix B.2), the initial dependent variables, the vector of variables used in column 8 of Tables 3-4, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Paap F-statistics.

Table B10: Robustness. Correlation Between Observed Subsidy-Related Variables and the IV. Local Spillovers and Complementarity

Dep.	1972-1979 or 1973-1980			
	Δasinh(Cum. credit)		Δasinh(Cum. export promotion)	
	(1)	(2)	(3)	(4)
$\text{IV}_{inj,t-2}^{\geq 100\text{km},t_0}$	0.05	0.05	2.51	2.51
	(1.48)	(1.48)	(2.62)	(2.62)
# Clusters	$86 \times 1{,}548$			
N	1,977	1,977	1,977	1,977
Fixed effects	Region, Sector, Group×Sector			
Business group sales share	✓	✓	✓	✓
Additional ctrl		✓		✓

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 coefficients obtained by regressing subsidy-related variables on the IV defined in equation (3.6). In columns 1-2 and 3-4, the dependent variables are changes in the inverse hyperbolic sine transformation of cumulative directed credit and contract values made in international trade fairs between 1972-1979 or 1973-1980, respectively. Columns 2 and 4 include the vector of variables used in column 8 of Tables 3-4. All specifications include business groups' predicted sales shares within region-sectors (equation (B.2), detailed in Appendix B.2), the initial dependent variables, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Paap F-statistics.

Table B11: Robustness. Placebo. Local Spillovers and Complementarity

Dep.	1970-1972 or 1971-1973					
	$\Delta \ln \text{Sale}_{it}$			$\Delta \mathbb{1}[\text{New Contract}_{it}]$		
	OLS	RF	IV	OLS	RF	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\text{Share}_{(-i)nj,t-2}$	0.05		1.17	0.03		-0.35
	(0.34)		(1.86)	(0.07)		(0.26)
$\text{IV}_{nj,t-2}^{\geq 100\text{km},t_0}$		0.30			-0.07	
		(0.50)			(0.06)	
KP-F			16.78			12.55
# clusters		73×830			86×1,395	
N	1,004	1,004	1,004	1,788	1,788	1,788
Fixed effects	Region, Sector, Group×Sector					
Business group sales share	✓	✓	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓	✓	✓

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 (3.5). Adopter shares and IV are defined in equations (3.4) and (3.6). In columns 1-3 and 4-6, the dependent variables are changes in log sales or dummies of making new adoption contracts between 1970-1972 or 1971-1973, respectively. In Columns 1-3, the sample consists of firms that never adopted technologies during the sample period, while in columns 4-6, the sample consists of all firms. All specifications include business groups' predicted sales shares within region-sectors (equation (B.2), detailed in Appendix B.2), the initial depedent variables, the vector of variables used in column 8 of Tables 3-4, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Paap F-statistics.

Table B12: Robustness. Spatial Correlation. Moran's I Statistics. Local Spillovers and Complementarity

Dep.	1972-1979 or 1973-1980											
	$\Delta \ln \text{Sale}_{it}$				ΔTFPR_{it}				$\Delta \mathbb{1}[\text{New Contract}_{it}]$			
Morans' I	75 km	100 km	150 km	200 km	75 km	100 km	150 km	200 km	75 km	100 km	150 km	200 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
z-score	−1.25	−0.94	−0.79	−0.67	−0.96	−0.83	−0.77	−0.70	−1.15	−0.86	−0.71	−0.64
p-val	[0.21]	[0.35]	[0.43]	[0.50]	[0.34]	[0.41]	[0.44]	[0.48]	[0.25]	[0.39]	[0.48]	[0.52]
N	1,492	1,492	1,492	1,492	842	842	842	842	1,977	1,977	1,977	1,977
Fixed effects	Region, Sector, Sector × Group											
Business group sales share	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table reports Moran's I statistics which test the presence of spatial auto-correlations upto different thresholds. Moran's I statistics are computed based on residuals from the regression models in equation (3.5). In columns 1-4, 5-8, and 9-12, the dependent variables are changes in log sales, revenue TFP, and dummies of making new contracts between 1972-1979 or 1973-1980, respectively. In columns 1-8, the sample consists of firms that never adopted technologies during the sample period, while in columns 9-12, the sample consists of all firms. In columns 5-8, the sample size decreases due to missing employment data. All specifications include business groups' predicted sales shares within region-sectors (equation (B.2), detailed in Appendix B.2), the initial dependent variables, the vector of variables used in column 8 of Tables 3-4, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Paap F-statistics.

Table B13: Robustness. Firm Entry and Exit. Local Spillovers and Complementarity

Dep.	Exit dummy in 1979 or 1980		Entry dummy in 1979 or 1980	
	(1)	(2)	(3)	(4)
$\Delta\text{Share}_{nj,t-2}$	-0.13	-0.02	0.03	0.03
	(0.67)	(0.71)	(0.18)	(0.20)
KP-F	15.90	14.61	28.25	35.41
# Clusters	$86 \times 2{,}502$	$86 \times 2{,}502$	$86 \times 3{,}360$	$86 \times 3{,}360$
N	4,118	4,118	6,231	6,231
Fixed effects	Region, Sector, Group×Sector			
Business group sales share	✓	✓	✓	✓
Additional ctrl		✓		✓

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 (3.5). The dependent variables are the exit and entry dummies in 1979 or 1980 in columns 1-2 and 3-4, respectively. Between 1972-1979, there were 1,800 firms operating in 1972. Out of 1,800, 932 firms were continuously operating in both 1972 and 1979 and 868 firms exited in 1980, whereas 2,288 firms entered in 1979. Between 1973-1980, there were 2,176 firms operating in 1973. Out of 2,176, 1,069 firms were continuously operating in both 1973 and 1980 and 1,107 firms exited in 1980, whereas 1,981 firms entered in 1980. The firms that continuously operated (927 and 1,062 firms in the two respective periods) serve as the estimation sample for spillover and complementarity regressions in Tables 3 and 4. Out of 1,989, 12 observations were dropped due to inclusion of fixed effects. Columns 2 and 4 include the the vector of additional controls used in column 8 of Tables 3-4. All specifications include business groups' predicted sales shares within region-sectors (equation (B.2), detailed in Appendix B.2), and region, sector, and group-sector fixed effects. KP-F is the Kleibergen-Paap F-statistics.

Table B14: Robustness. Alternative Inference. Local Spillovers and Complementarity

Dep.	1972-1979 or 1973-1980		
	$\Delta \ln \text{Sale}_{it}$	ΔTFPR_{it}	$\Delta\mathbb{1}[\text{New Contract}_{it} > 0]$
	(1)	(2)	(3)
Coefficient $\Delta\text{Share}_{nj,t-2}$			
Baseline p-val	[< 0.01]	[< 0.01]	[0.03]
Bootstrap p-val (Young, 2022)	[0.02]	[0.06]	[0.07]
Spatial HAC p-val (Conley, 1999)			
Bandwidth 75 km	[< 0.01]	[< 0.01]	[0.04]
Bandwidth 100 km	[< 0.01]	[< 0.01]	[0.03]
Bandwidth 150 km	[< 0.01]	[< 0.01]	[< 0.01]
Alternative clustering p-val			
Region	[< 0.01]	[< 0.01]	[0.03]
Region-sector	[< 0.01]	[0.02]	[< 0.05]
Two-way, region-sector & group	[< 0.01]	[< 0.01]	[< 0.05]
Weak-IV-robust inference			
Anderson-Rubin test p-val (Andrews et al., 2019)	[< 0.01]	[< 0.01]	[0.03]
Two-step AR-CI 95% (Andrews, 2018)	{1.10, 4.24}	{0.69, 2.81}	{0.16, 1.76}
N	1,492	842	1,977
Fixed effects	Region, Sector, Sector×Group		
Business group sales share	✓	✓	✓
Additional ctrl	✓	✓	✓

Notes. This table reports p-values and confidence intervals, corresponding to the null that the coefficient of $\Delta\text{Share}_{(-i)nj,t-2}$ is zero, based on alternative inference procedures. P-values and confidence intervals are in brackets and braces, respectively. The baseline p-values are based on standard errors two-way clustered at the region and business group levels. The bootstrap p-values are obtained by applying wild bootstrap. Spatial HAC is inference based on spatial heteroskedasticity autocorrelation consistent standard errors following Conley (1999). Two-step AR-CI 95% is the 95% confidence interval of the Anderson-Rubin test based on Andrews (2018). In columns 1, 2, and 3, the dependent variables are changes in log sales, revenue TFP, and dummies of making new adoption contracts between 1972-1979 or 1973-1980, respectively. In columns 1-2, the sample consists of firms that never adopted technologies, while in column 3, the sample consists of all firms. In column 2, the sample size decreases due to missing employment data. All specifications include the vector of controls used in column 8 of Tables 3-4, region, sector, group-sector fixed effects, and the initial dependent variables. KP-F is the Kleibergen-Paap F-statistics.

Table B15: Robustness. Alternative Outcomes, Lag, and Estimation Samples, and Omitting y_{it_0}. Local Spillovers

Robustness	Alternative outcomes				Omitting y_{it_0}	Alternative lag	Alternative samples		
Dep.	$\Delta \text{TFPR}_{it}^{\text{OP}}$	$\Delta \ln \text{Labor prod}_{it}$	$\Delta \mathbb{1}[\text{Export}_{it} > 0]$	$\Delta \ln \text{Fixed asset}_{it}$	$\Delta \ln \text{Sale}_{it}$				
Samples.	Never-adopter						Non-missing emp.	Excl. business group firms	Excl. regions with industrial complex
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\text{Share}_{(-i)nj,t-2}$	0.76**	1.12*	1.17***	4.59***	1.54		3.37***	2.60***	2.06***
	(0.38)	(0.59)	(0.39)	(1.13)	(0.97)		(0.99)	(0.86)	(0.77)
$\Delta\text{Share}_{(-i)nj,t-3}$						2.35***			
						(0.75)			
KP-F	20.00	20.02	16.35	16.14	16.25	218.99	18.67	16.64	14.01
# Clusters	67 × 742	67 × 742	79 × 1,294	79 × 1,291	79 × 1,294	79 × 1,294	67 × 742	79 × 1,221	76 × 999
N	824	824	1,492	1,489	1,492	1,492	824	1,360	1,117
Fixed effect	Region, Sector, Group×Sector								
Business group sales share	✓	✓	✓	✓	✓	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓	✓	✓	✓	✓	✓

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 (3.5). Adopter shares $\text{Share}_{(-i)nj,t-h}$ and the IV are defined in equations (3.4) and (3.6). The sample consists of firms that never adopted technologies during the sample period. In columns 1, 2, 3, 4, and 5-9, the dependent variables are changes in revenue TFP based on Olley and Pakes (1996), log labor productivity, dummies of exporting, log fixed asset, and log sales, respectively, between 1972-1979 or 1973-1980. In columns 1-3, the sample size decreases due to missing data. All specifications, except for column 5, include the initial dependent variables. In column 6, we consider the alternative lag of 3. We consider the alternative estimation sample with non-missing employment in column 7; the sample that excludes firms affiliated with business groups in column 8; and the sample that exclude firms in regions with the industrial complexes in column 9. All specifications include the business group sales shares control (equation (B.2), detailed in Appendix B.2), the vector of additional controls used in column 8 of Tables 3-4, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Papp F-statistics.

Table B16: Robustness. Alternative Lags and Estimation Samples, and Omitting y_{it_0}. Local Complementarity

Robustness	Omitting y_{it_0}	Alternative lag	Alternative sample		
Dep.	$\Delta\mathbb{1}$[New Contract$_{it}$ > 0] 1972-1979 or 1973-1980				
Sample	Full sample		Non-missing emp.	Excl. business group firms	Excl. regions with industrial complex
	(1)	(2)	(3)	(4)	(5)
ΔShare$_{(-i)nj,t-2}$	1.19***		0.95**	0.66*	1.13**
	(0.44)		(0.45)	(0.39)	(0.45)
ΔShare$_{(-i)nj,t-3}$		0.41*			
		(0.23)			
KP-F	17.51	140.11	13.96	10.95	11.57
# Clusters	$86 \times 1{,}548$	$86 \times 1{,}548$	76×950	$83 \times 1{,}454$	$84 \times 1{,}194$
N	1,977	1,977	1,177	1,701	1,430
Fixed effect	Region, Sector, Group×Sector				
Business group sales share	✓	✓	✓	✓	✓
Additional ctrl	✓	✓	✓	✓	✓

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 (3.5). Adopter shares Share$_{(-i)nj,t-h}$ and the IV are defined in equations (3.4) and (3.6). The dependent variables are changes in dummies of making new adoption contracts between 1972-1979 or 1973-1980. In columns 1-2, the sample consists of all firms. We consider the alternative estimation sample with non-missing employment in column 3; the sample that excludes firms affiliated with business groups in column 4; the sample that exclude firms in regions with the industrial complexes in column 5. All specifications include the business group sales shares control (equation (B.2), detailed in Appendix B.2), the initial levels of dependent variables, the vector of additional controls used in column 8 of Tables 3-4, and region, sector, and sector-group fixed effects. KP-F is the Kleibergen-Papp F-statistics.

C. Simple Model

C.1 Derivation of Equations (4.3) and (4.4)

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

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

Note that $\frac{L}{Q_t} = \frac{\int l_{it} \mathrm{d}i}{Q_t} = \int \frac{y_{it}}{Q_t}\frac{1}{z_{it}}\mathrm{d}i = \int \frac{1}{z_{it}}\left(\frac{p_{it}}{P_t}\right)^{-\sigma}\mathrm{d}i$ 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 $Q_t = [\int z_{it}^{\sigma-1}\mathrm{d}i]^{\frac{1}{\sigma-1}} L$. From the assumption of Pareto distribution, we can further derive that

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

where the second equality is derived from $(\lambda_t^T)^{-\frac{1}{\theta}} = \bar{\phi}_t^T$. Using that

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

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),

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

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:

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

C.2 Proofs of Propositions

C.2.1 Proof of Proposition 1

Proposition 1(i) (Uniqueness). 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) (Comparative statics). Taking the derivative of equation (C.8) with respect to η and δ, we obtain

$$\frac{\partial G}{\partial \eta} = A(\hat{\lambda}_t^T)^{3-2\sigma} f(\lambda_{t-1}^T) L \frac{(\sigma-1)\eta^{\sigma-2}}{\sigma F^T} \frac{\theta}{\tilde{\theta}} \left[\frac{1}{\sigma-1} (\eta^{\sigma-1}-1)(\hat{\lambda}_t^T)^{\frac{\tilde{\theta}}{\theta}} + 1 \right] > 0, \tag{C.6}$$

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

Applying the implicit function theorem and using the signs of equations (C.9), (C.7), and (C.6), 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(iii) (Dynamic complementarity). We apply the implicit function theorem. Let

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

Taking the derivative of equation (C.8) with respect to λ_t^T, we obtain

$$\frac{\partial G}{\partial \hat{\lambda}_t^T} = \underbrace{\frac{2-\sigma}{\sigma-1}}_{<0} \times \underbrace{A(\hat{\lambda}_t^T)^{3-2\sigma}(\hat{\lambda}_t^T)^{-\frac{\sigma-1}{\theta}} f(\lambda_{t-1}^T) \frac{(\eta^{\sigma-1}-1)^2}{\sigma F^T} L}_{>0} - \underbrace{\frac{\sigma-1}{\theta}(\hat{\lambda}_t^T)^{-\frac{\tilde{\theta}}{\theta}}}_{>0} < 0, \tag{C.9}$$

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

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

Applying the implicit function theorem and using the signs of equations (C.9) and (C.10), 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(iv) (Multiple steady states). 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,

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

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

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

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

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

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.9), (C.10), (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

$$A(1;\eta)^{2-\sigma} f(\hat{\lambda}^T;\underline{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}L - 1 = 0$$

for $\hat{\lambda}^T = 1$. Similarly, holding other parameters constant, there exists $\underline{\eta}$ that satisfies

$$A(1;\underline{\eta})^{2-\sigma} f(\hat{\lambda}^T;\delta)\frac{(\underline{\eta}^{\sigma-1}-1)}{\sigma F^T}L - 1 = 0$$

for $\hat{\lambda}^T = 1$. Also, because $\hat{\lambda}^T_t$ is strictly convex in λ^T_{t-1}, 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.8); that is, $\bar{\delta}$ and $\bar{\eta}$ satisfy $A(\hat{\lambda}^T;\eta)^{2-\sigma} f(\hat{\lambda}^T;\bar{\delta})\frac{(\eta^{\sigma-1}-1)}{\sigma F^T}L - \hat{\lambda}^T = 0$ and $A(\hat{\lambda}^T;\bar{\eta})^{2-\sigma} f(\hat{\lambda}^T;\delta)\frac{(\bar{\eta}^{\sigma-1}-1)}{\sigma F^T}L - \hat{\lambda}^T = 0$ 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 $\lambda^T = \lambda^T_t = \lambda^T_{t-1} = 1$ 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) (Welfare). The welfare of household is $\frac{w_t+\Pi_t/L}{P_t}$ where Π_t are the aggregate profits summed across all firms in the economy. Note that

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

where the last equality comes from equations (C.2) and (C.3). The above equation implies that welfare in each period $\frac{w_t+\Pi_t/L}{P_t}$ is equal to $f(\lambda^T_{t-1})A(\lambda^T_t)$ 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.

C.2.2 Proof of Proposition 2

Proof of Proposition 2 (i) (Big push). Suppose an economy features multiple steady states S^{Pre}, S^{U}, and S^{Ind} and is initially stuck in the underdevelopment region $\lambda_{t_0} \in [0, S^{\text{U}})$. 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 an subsidy rate for adopters. Firm charges price $p_{it} = \frac{\mu(1-s_{it})w_t}{z_{it}}$. The cutoff is

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

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

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

The equilibrium share of adopters can be expressed as

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

Similarly with subsidies to 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

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

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}.

Proof of Proposition 2(ii) (Market size). By applying the implicit function theorem, it can be shown that $\frac{\partial \lambda_t^T}{\partial L} < 0$, implying that higher L shift the short-run equilibrium curve downward and therefore $\frac{\partial S^U}{\partial L} < 0$ and $\frac{\partial \underline{S}}{\partial L} < 0$. □

C.3 Source of Dynamic Complementarity and Comparison with Buera et al. (2021)

Comparison with Buera et al. (2021). Suppose there are no spillovers ($\delta = 0$). Our simple model in Section 4 collapses to a special case of the full model presented by Buera et al. (2021), excluding idiosyncratic distortions and intermediate inputs in production. Our model does not admit multiple equilibria within each period due to the assumption that $\sigma > 2$ (Assumption 1(i)). Without spillovers, the previous adopter shares do not affect the current equilibrium and the equilibrium adopter share can be expressed as

$$\lambda_t^T = \left(\frac{(\eta^{\sigma-1} - 1)}{\sigma F^T} LA(\lambda_t^T)^{2-\sigma}\right)^{\frac{\theta}{\sigma-1}}.$$

Because $\sigma > 2$, the right hand side is strictly decreasing in λ_t^T, implying that there is always a unique equilibrium. Note that when $\sigma < 2$, because the right hand side becomes strictly increasing in λ_t^T, there can be multiple equilibria, the possibility studied in Buera et al. (2021).

Fixed adoption costs in units of labor. In the case when fixed adoption costs are in units of labor, the model does not exhibit dynamic complementarity, regardless of the presence of spillovers. The key equations for the cutoff productivity and the equilibrium shares are given by:

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

The equilibrium share is uniquely determined regardless of the values of λ_{t-1}^T. This is because higher previous shares λ_{t-1}^T increase overall productivity in t through spillovers, which in turn, leads to higher demand for labor. This increased demand raises the equilibrium wage, resulting in higher adoption costs $w_t F^T$. These increased costs exactly offset the larger incentives for adoption induced by spillovers.

C.4 Possible Microfoundations for Adoption Spillovers

This subsection provides two possible microfoundations for spillovers. For both cases, we consider a closed economy setup with one sector and one region as in the simple model.

Local diffusion of knowledge. A firm receives exogenous productivity $\tilde{\phi}_{it}$ and makes two decisions each period: whether to adopt modern technology T_{it} and the level of innovation a_{it} similar to Desmet and Rossi-Hansberg (2014). The profit maximization problem is given by:

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

where $\tilde{\eta}$ governs direct productivity gains from 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 arise from the fact that the innovation costs decrease with the previous adopter share $\partial g(\lambda_{t-1}^T)/\partial \lambda_{t-1}^T < 0$, reflecting that more local firms can learn from 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 the maximization problem.

A firm's optimal level of a_{it} is characterized as

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

Because $-1/\tilde{\alpha} > 0$ and $(\sigma-1)/\tilde{\alpha} > 0$, a_{it} increases in λ_{t-1}^T, 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:

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

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

This microfoundation aligns with a case study from (Kim, 1997, p. 182-184). Wonil Machinery Work (henceforth Wonil) started its business as a small hot and cold rolling mill producer. One local firm imported a more sophisticated 4-high nonreverse cold rolling mill, which was a technology widely used in developed countries. Wonil's engineers had an opportunity to observe how the local firm was operating these state-of-the-art mills and obtained technical information indirectly from this local firm. From this opportunity, Wonil developed its own 4-high cold rolling mill blueprints and began producing them.

Learning externalities and labor mobility. There is a unit measure of engineers and firm owners. Engineers live in two periods: childhood and adulthood. Once they reach adulthood in the second period, they give birth to a child. They only consume and work during their adulthood. Engineers who work in firms that adopt new technologies pass their knowledge to their children. This parental learning increases the engineering skills of the children as they grow up, enhancing their skills by a factor of $\gamma_1 > 1$. If parents do not work in firms with foreign technology, their children's engineering skills remain at a level of 1.

Engineers and owners are randomly matched one-to-one (Acemoglu, 1996). After matching, production takes place, and the two parties jointly maximize profits. The profits generated by this match are divided between engineers and owners based on Nash bargaining, with managers receiving a proportion of $\tilde{\beta}$. Since owners make adoption decisions before a match occurs, they must base these decisions on anticipated profits. Due to the random matching process, owners are paired with high-skilled engineers with a probability of λ_{t-1}^T and low-skilled engineers with a probability of $1 - \lambda_{t-1}^T$.

A firm's maximization problem is

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

This can be re-written as

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

where $\tilde{f}(\lambda_{t-1}^T) = [\lambda_{t-1}^T(\gamma_1^{\sigma-1} - 1) + 1]^{\frac{1}{\sigma-1}}$ can be mapped to $f(\lambda_{t-1}^T)$ of the simple of in Section 4. This diffusion through moility channel is consistent with the case of POSCO in Section B.1.

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. The price index is given by

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

Firm. Firms have the following CRS production technology:

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

Unit costs of input bundles are

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

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 after maximizing over T_{it} and x_{it} is:

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

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:

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

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

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

A share of adopters is expressed as

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

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 $M^x_{njt} = M_{nj}\lambda^x_{njt}$.

Preference. Representative households have Cobb-Douglas preferences:

$$\ln C_{nt} \qquad C_{nt} = \prod_{j=1}^{J} C^{\alpha_j}_{njt}$$

subject to the budget constraints: $P_{nt}C_{nt} = (1 - \tau^w_t + \bar{\pi}_t)w_{nt}$. Their total income $(1 - \tau^w_t + \bar{\pi}_t)w_{nt}$ is the sum of after-tax wages $(1 - \tau^w_t)w_{nt}$ and dividend income $\bar{\pi}_t w_{nt}$, where total profits and government spending are distributed across households in regions proportional to their labor incomes. The corresponding price index is $P_{nt} = \prod_{j=1}^{J} P^{\alpha_j}_{njt}$.

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

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

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

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

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

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

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

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

Regional gross output for domestic expenditures R^d_{njt} and the total value of exports R^x_{njt} are

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

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

Market clearing. Labor market clearing implies

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

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

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

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 paths of the fundamentals $\{\phi^{min}_{njt}, P^f_{jt}, D^x_{jt}\}$, 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 $\{\tau^w_t\}$, 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) firm adoption decisions endogenously determine a path of the state variable λ^T_{njt}.*

E. Quantification

E.1 Calibration Procedure

Data inputs. The quantitative exercises require the following data inputs:

1. Initial adopter shares $\{\lambda^{T,\text{Data}}_{nj,68}\}_{n\in\mathcal{N}, j\in\mathcal{J}^T}$ and initial population $\{L^{\text{Data}}_{n,72}\}_{n\in\mathcal{N}}$
2. Region-sector gross output $\{R^{\text{Data}}_{njt}\}_{n\in\mathcal{N}, j\in\mathcal{J}, t\in\{72,76,80\}}$
3. Sectoral exports and import shares $\{\text{EX}^{\text{Data}}_{jt}, \pi^{f,\text{Data}}_{jt}\}_{j\in\mathcal{J}, t\in\{72,76,80\}}$
4. Sectoral PPI changes between t and $t-1$, for $t \in \{76, 80\}$
5. Aggregate real GDP growth between t and $t-1$, for $t \in \{76, 80\}$
6. 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 calibrate values of $\mathbf{\Theta}^{\text{M}}$, $\bar{s}$, and $\mathbf{\Psi}_t$ using the following algorithm:

1. Guess parameters.
2. Guess fundamentals $\{c_{fj}, D_{fj}\}_{j\in\mathcal{J}}$, and $\{\phi^{\min}_{nj}\}_{n\in\mathcal{N}, j\in\mathcal{J}}$.
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 $\{D_{jt}^{f\prime}\}$ by fitting the export intensities of the model to those in the data $\frac{\mathrm{EX}_{jt}^{\mathrm{Data}}}{\sum_n R_{njt}^{\mathrm{Data}}}$.

(b) Update $\{P_{jt}^{F\prime}\}$ by fitting the import shares of the model to those in the data $\pi_{jt}^{f,\mathrm{Data}}$.

(c) For each sector, update $\{\phi_{njt}^{\min\prime}\}$ relative to the reference region until the shares of regional gross output exactly match the data counterparts $\frac{GO_{njt}^{\mathrm{Data}}}{\sum_m GO_{mjt}^{\mathrm{Data}}}$. Within each sector, the regional gross output distribution only identifies the relative levels, so we normalize the Pareto lower bound parameters of the reference region n_0 to 1 for each sector and period.

(d) We recover the absolute levels of $\{\phi_{n_0 jt}^{\min\prime}\}$ using sector PPI and real GDP growth. In the model, we construct PPIs as weighted averages of regional price indices, weighted by the initial regional gross output in 1970. Because PPIs only identify relative changes of sectoral productivity growth relative to the reference sector, we identify the relative sector's Pareto lower bound using real GDP growth. The 1970 Pareto lower bounds of the reference regions are set to 1.

4. After updating the geographic fundamentals, given values of parameters and subsidies, we evaluate the objective function.
5. We iterate steps 1-4 until we find values of $\{\hat{\mathbf{\Theta}}^{\mathrm{M}}, \hat{\mathbf{s}}_t\}$ that minimize the objective function.

E.2 Spatial Mobility

We extend the baseline quantitative model to incorporate spatial mobility of households. At the beginning of each period, households make *myopic* migration decisions that maximizes their static utility in each period, following (Peters, 2022). After relocating, they supply labor and earn wages in their new regions. Households choose where to live based on factors such as amenities, real income, migration frictions, and preference shocks:

$$\max_n \left\{U_{mnt}(\varepsilon_{mnt})\right\}, \qquad \text{where} \qquad \mathcal{U}_{nmt}(\varepsilon_{nmt}) = V_{mt}C_{mt}d_{nm}\varepsilon_{nmt}.$$

V_{mt} is an exogenous amenity in region m that makes regions more or less attractive to live in, d_{nm} is the utility cost of moving from n to m, and ε_{nmt} is a preference shock drawn independently and identically from a Fréchet distribution with the shape parameter ν: $F(\varepsilon) = \exp(\varepsilon^{-\nu})$. The parameter ν is the migration elasticity that governs how responsive migration flows are to real income changes in destination regions. Population L_{nt} becomes a state variable, in addition to adopter shares λ_{njt}^{T}. The share of households moving from n to m in t is given by:

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

Population evolves as a state variable according to $L_{nt} = \sum_m \mu_{nm,t-1}L_{m,t-1}$.

Calibration. Because each period corresponds to 4 years, we set $\nu = 0.5$ based on the migration elasticity of 0.5 at the annual frequency estimated by Choi (2024), which also aligns with the long-run value of 2 of (Peters, 2022). We parametrize migration costs as $d_{nm} = (\text{Dist}_{nm})^{\zeta}$. With the calibrated value of ν, we estimate a gravity equation for migration flows $\mu_{nm} = \exp(\nu\zeta\text{Dist}_{nm} + \delta_n + \delta_m)\varepsilon_{nmt}$. To address attenuation bias arising from statistical zeros, we employ the PPML estimation. We use migration flow data for individuals aged 20 to 55 from 1990 to 1995 obtained from the 1995 Population and Housing Census, which is the closest available data to the sample period. We obtain $\nu\zeta = 1.39$. Given these migration parameters, amenities are backed out by fitting population distributions for the years of 1972, 1976, and 1980. Because amenities are identified upto a normalization, we set V_{nt} to 1 in the reference region for each period.

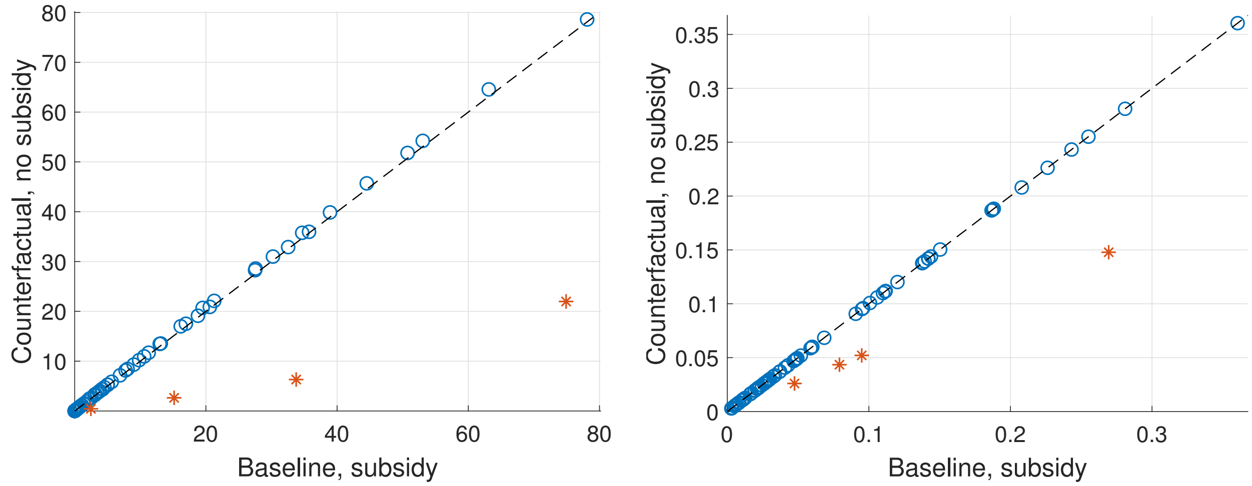
E.3 Additional Figures and Tables

Table E1: Additional Non-Targeted Moments

	Model			Data		
Dep.	Emp (1)	Export (2)	Exporter share (3)	Emp (4)	Export (5)	Exporter share (6)
λ^T_{njt}	0.256***	0.294**	0.702***	0.282*	0.310***	0.549***
	(0.066)	(0.117)	(0.154)	(0.142)	(0.092)	(0.166)
Adj. R^2	0.91	0.55	0.77	0.73	0.78	0.37
N	258	258	258	258	258	258

Notes. This table presents the non-targeted moments of the model. The dependent variables are each region's heavy manufacturing employment in columns 1 and 4, export in columns 2 and 5, and shares of exporters in columns 3 and 6. Employment and exports are normalized by corresponding sum of total manufacturing sectors. All specifications include region fixed effects.

Figure E1: Local Effects of the Big Push

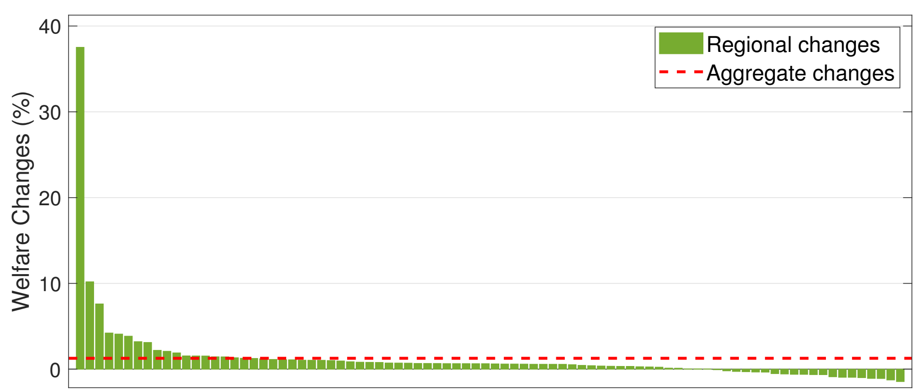


Steady state local heavy mfg.

A. GDP share B. Productivity

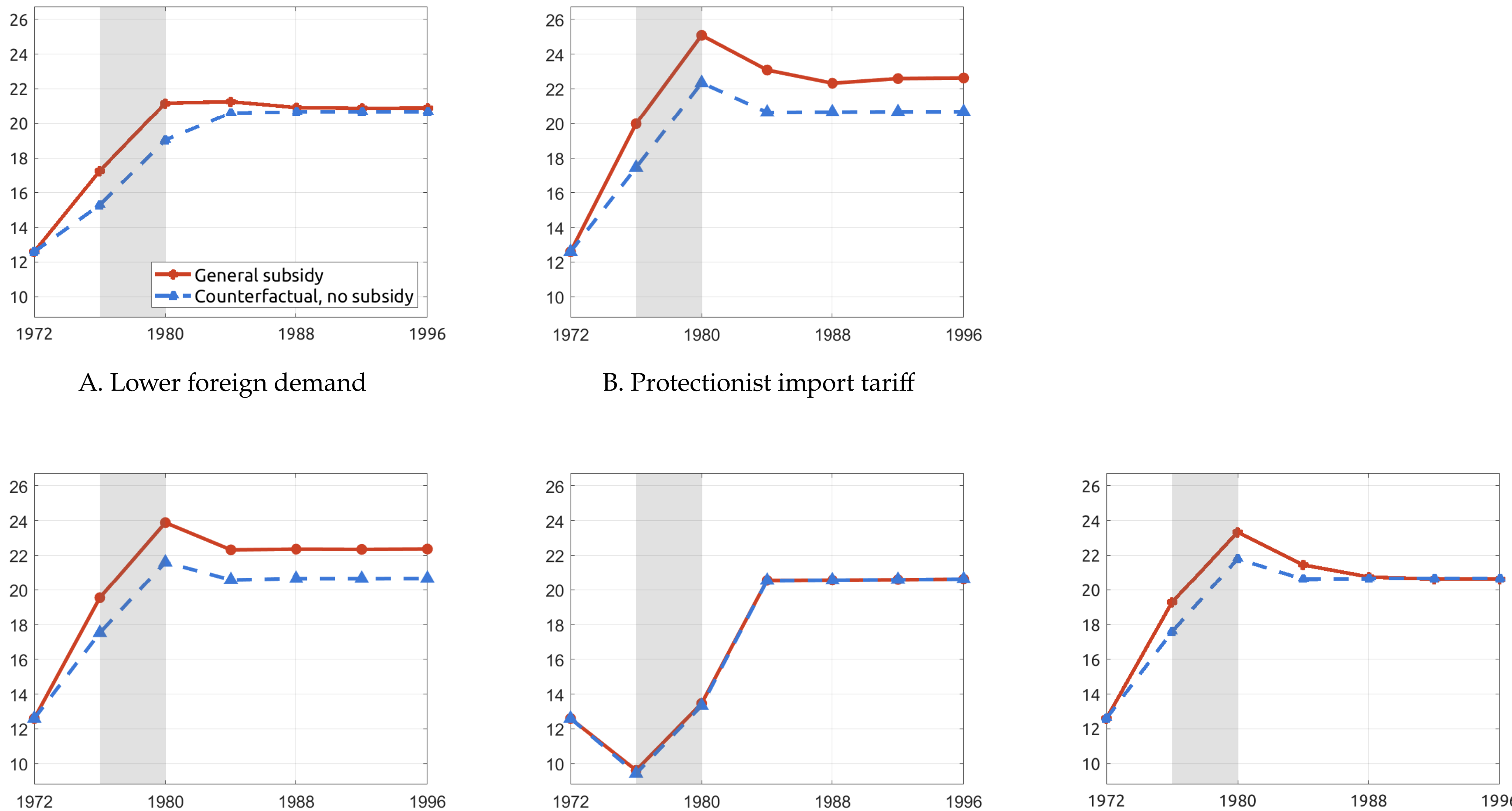
Notes. Panels A and B illustrate each region's GDP shares and productivity $M_{nj}[\int z_{it}(\phi)^{\sigma-1}dG_{njt}(\phi)]^{1/(\sigma-1)}$ of the heavy manufacturing sector in the steady states of the baseline and counterfactual economies (x and y axes). Each dot represents a region, with dots located below the 45-degree line, colored red, indicating regions with higher steady state GDP shares and productivity in the baseline than the counterfactual.

Figure E2: Regional Welfare Distribution



Notes. This figure presents the regional welfare distribution. The horizontal red dashed line denotes for the aggregate welfare changes. 66 and 20 out of 86 regions experience welfare gains and losses, respectively.

Figure E3: Alternative Scenarios for Market Access and Other Policies. Aggregate Effects of the Big Push. Baseline vs. Counterfactual



A. Lower foreign demand

B. Protectionist import tariff

C. No transportation improvements

D. No internal trade

E. Joint (A + B + C)

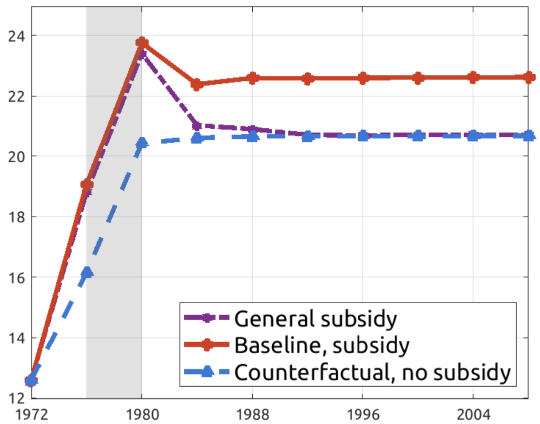
Notes. This figure plots the time paths of the heavy manufacturing sector's GDP shares of the baseline and counterfactual economies under alternative scenarios for market access and other policies. Panel A considers a scenario with 25% lower foreign demand. Panel B examines the impact of a protectionist tariff scheme, where tariffs increase by 40% between 1972 and 1980. Panel C reverses the 66% reductions in travel time resulting from the highway construction. Panel D explores the impact of prohibiting internal trade within the heavy manufacturing sector. Finally, Panel E considers the combined effects of the scenarios in Panels A, B, and C.

Table E2: Alternative Subsidy Scheme. Randomized Subsidy Regions

Dep.	$\triangle$ ln Heavy mfg. GDP shares				$\triangle$ Welfare			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. ln Dist. Port$_n$	-0.63^{***}				-0.29^{***}			
	(0.12)				(0.06)			
Avg. ln MA$_{n,heavy,72}$		0.30^{*}				0.18^{**}		
		(0.16)				(0.07)		
Avg. ln $\phi^{\min}_{n,heavy,72}$			-0.15				-0.17	
			(0.39)				(0.18)	
Avg. ln $L_{n,72}$				-0.18				-0.06
				(0.16)				(0.07)
N	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Notes. We randomize which regions receive subsidies while holding the total number of subsidized regions constant at 35, as in the baseline calibration. This exercise is repeated 1,000 times. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the OLS estimates of the following regression model: $y_b = \bar{\mathbf{X}}_b' \boldsymbol{\beta} + \varepsilon_b$, where $\bar{\mathbf{X}}_b = (1/|\mathcal{N}^s_b|) \times \sum_{n \in \mathcal{N}^s_b} \mathbf{X}_{n,72}$, $\bar{\mathbf{X}}_b$ is the average of observable $\mathbf{X}_{n,72}$ across the subsidized regions, and $\mathcal{N}^s_b$ is the set of 35 subsidized regions in simulation b. The dependent variables are steady state differences in the log of the heavy manufacturing sector's GDP shares and welfare changes between the baseline and counterfactual economies. Avg. ln Dist. Port$_n$ is the average of the log minimum distance to the nearest port of subsidized regions in each simulation; Avg. ln MA$_{n,heavy,72}$ is the average log initial market size of heavy manufacturing firms in 1972 (defined in equation (3.7)); Avg. ln $\phi^{\min}_{n,heavy,72}$ is the average log natural advantage; and Avg. ln $L_{n,72}$ is the average log initial population in 1972.

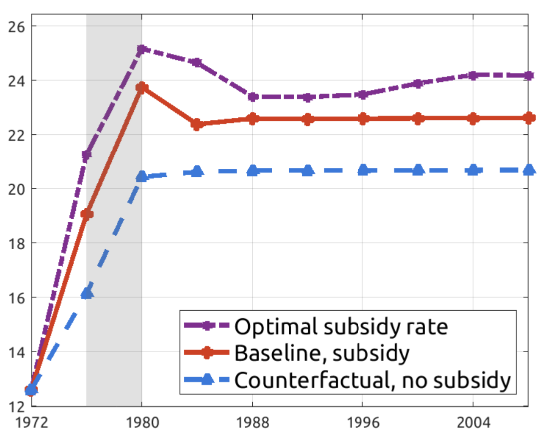
Figure E4: Alternative Subsidy Scheme. General Subsidy



Heavy mfg. GDP share (%)

Notes. This figure presents the heavy manufacturing sector's GDP shares in scenarios with general subsidies (purple), baseline adoption subsidies (red), and no subsidies (blue).

Figure E5: Alternative Subsidy Scheme. Optimal Subsidy Rate



Heavy mfg. GDP share (%)

Notes. This figure presents the heavy manufacturing sector's GDP shares with the optimal subsidy rate of 12% that maximizes aggregate welfare (purple), baseline adoption subsidies (red), and no subsidies (blue).

Table E3: Robustness. Statistical Uncertainty

0.5 std higher (1)	Baseline (2)	0.5 std. lower (3)	1 std. lower (4)	1.5 std. lower (5)	Lower 90% CI (6)	Lower 95% CI (7)
Panel A. Spillover parameter δ						
Parameter value $(\sigma-1)\delta$						
3.4	2.7	2.35	2.0	1.70	1.48	1.24
Δ Heavy mfg. GDP share (%)						
2.35	1.95	1.77	1.66	1.36	0	0
Does the big push occur?						
Y	Y	Y	Y	Y	N	N
Panel B. Direct gain parameter η						
Parameter value η						
1.2	0.9	0.75	0.60	0.45	0.40	0.30
Δ Heavy mfg. GDP share (%)						
0	1.95	1.69	1.47	1.36	1.25	1.20
Does the big push occur?						
N	Y	Y	Y	Y	Y	Y

Notes. This table reports the sensitivity analysis regarding statistical uncertainty of the point estimates of the parameters η and δ that govern strength of spillovers and direct gains, respectively. We consider values within the 95% confidence intervals of the point estimates (η for column 1 of Panel B of Table 2 and δ for column 3 of Panel A of Table 3). For each different value, the geographic fundamentals and remaining parameters are re-calibrated.

Table E4: Robustness. Spatial Mobility and Sensitivity Analysis for Alternative Parameter Values

Baseline	Spatial	Alternative parameter values			
	Mobility	$\sigma = 3$	$\sigma = 5$	$\theta = 1.02$	$\theta = 1.10$
(1)	(2)	(3)	(4)	(5)	(6)
Δ Heavy mfg. GDP share (%)					
1.95	2.72	2.95	1.22	1.99	1.86
Does the big push occur?					
Y	Y	Y	Y	Y	Y

Notes. This table reports robustness exercises with spatial mobility (col. 2) and the sensitivity analysis under alternative sets of the externally parameters (col. 3-6). For each alternative set, the geographic fundamentals and remaining parameters are re-calibrated. Appendix E.2 explains the extended model with spatial mobility and its calibration procedure in detail.