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

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**Abstract**

We study how temporary subsidies for adoption of modern foreign 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 temporary subsidies shifted its economy to a more industrialized steady state, increasing heavy manufacturing's GDP share by 27% and export intensity by 39%. Larger market access and lower idiosyncratic distortions amplified the effects of these subsidies, as the gains from adoption increase with firm scale.

*Keywords*: big push, industrialization, coordination failure, complementarity, local spillover, market access
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# 1. Introduction

Since Rosenstein-Rodan (1943) and Hirschman (1958), coordination failures in the adoption of modern technology have been viewed as significant barriers to industrialization. These failures arise when firms' adoption decisions are interdependent, with private returns from modern technology increasing as more firms adopt. Such failures can lead to multiple states, leaving an economy trapped in a low-adoption state. A temporary *big push* policy intervention could overcome these failures by shifting the economy toward a welfare-improving, high-adoption state.[1] Despite its theoretical appeal, its real-world relevance remains underexplored due to the lack of quantification based on credible evidence and the difficulty of measuring technology. What are necessary preconditions for a successful big push? What makes such an intervention more likely to succeed?

This paper empirically and quantitatively examines the possibility of industrialization through a big push in technology adoption using novel historical microdata. Our analysis focuses on South Korea's large-scale policy, implemented between 1973 and 1979, which temporarily subsidized the adoption of modern technology in heavy manufacturing as part of broader industrial support programs. This period is notable because it experienced one of the most rapid industrialization episodes in world history during this relatively short implementation window.

Our main contributions are threefold. The first is our novel data collection effort on firm-level adoption of modern technologies during this rapid industrialization period. Second, using the novel dataset, we provide causal evidence on the firm-level effects of technology adoption, which align with coordination failures and the big push hypothesis. We estimate the 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

[1] In broader development contexts, the big push often involves multiple coordinated interventions. In our setting, the big push refers to temporary subsidies that trigger coordinated technology adoption, moving the economy above a threshold to a higher welfare state.

when other local firms have already adopted. Third, we develop a quantitative model, in which two key parameters that govern private returns from adoption and externality due to spillovers—preconditions for the presence of the multiplicity—are tightly pinned down by the empirical estimates. These two parameters serve as preconditions for the big push. 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 significantly amplified the effects of the big push.

[Insert Figure 1 here]

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 relative to the global frontier, foreign sources were the main channel for acquiring modern technologies. The dataset was manually constructed by digitizing contract documents that firms were required to file with the government authorities. In our context, technology adoption refers to the transfer of ideas, such as blueprints or training services, related to 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 heavy manufacturing GDP share begin to rise, increasing from 6% to 13% during the policy period. This was accompanied by a significant influx of new technologies in this sector through adoption contracts with foreign firms, resulting in fourfold increases in new contracts. Even after the policy ended, the economy continued to specialize in heavy manufacturing.

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 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 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 adopt 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 61% and revenue total factor productivity (TFPR) by 101%.

Our second finding is local spillovers from adoption. We regress growth in sales or TFPR 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, we propose an IV strategy based on the spatial networks of business groups with multiple firms across regions. Specifically, we use group-level technology adoption decisions from outside the region as exogenous shifters for adoption shares within the region 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 TFPR for non-adopters.

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 coordination failures in the adoption of modern technology. 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, suggesting coordination failures. Furthermore, the second finding on local spillovers points to potential positive externalities from adoption, indicating 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 this 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 temporary 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 the quantitative analysis, we extend the simple model to include internal and international trade, idiosyncratic distortions, time-varying fundamentals, and input-output linkages, allowing us to capture contemporaneous policies and financial frictions prevalent in low-income countries. The model is calibrated with firm- and region-level data: key parameters governing multiple steady states are mapped to reduced-form estimates, while the rest are calibrated by the method of moments. The model matches both targeted and non-targeted moments, notably reproducing the positive relationship between regional adoption and market access.

Subsidies are calibrated by the method of moments by targeting the increase in average adopter shares during the policy compared to their pre-policy levels. Because subsidies were only provided during the policy periods, these moments identify the subsidy rate. The calibrated rate implies that adopters received subsidies equal to 6% of input expenditures. On average, about 0.6% of GDP was spent on these subsidies.

Using the calibrated model, we evaluate South Korea's industrialization trajectory without the big push. In a counterfactual without subsidies, South Korea would have converged to a less-industrialized steady state, with heavy manufacturing's GDP share and export intensity 27% and 39% lower, respectively. The big push raised aggregate welfare by 14.6% but generated uneven regional welfare effects, from −1.2% to 83.8%. These uneven effects reflect two opposing forces: productivity gains in some regions lowered prices elsewhere through trade linkages, while also intensifying domestic competition.

The effects of the big push weakened under lower market access and worsened distortions due to the complementarity between firm scale and gains from the adoption. We consider scenarios where these factors are temporarily adjusted only during the policy period while post-1980 levels remain unchanged. Holding tariffs or foreign demand at initial levels reduced the effects by 5% and 15%. Worsening distortions—either by taxing more productive firms more heavily or raising overall distortions—also weakened the effect. These results highlight the role of market access and complementary policies, such as export promotion and financial reforms, in amplifying the big push.

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; Redding et al., 2011; Diodato et al., 2022; Alvarez et al., 2023; Becko, 2023; Crouzet et al., 2023; Garg, 2025; Lind, 2025). 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. We extend their model to an open economy with multiple regions. Kline and Moretti (2014), Moneke (2020), and Cerrato and Filippucci (2025) study regional development programs in the US, Ethiopia, and Italy, combining reduced-form evidence and structural models. Demir et al. (2024) study complementarities in quality upgrading through assortative matching in production network. Unlike these studies, our data allow us to directly measure firm-level technology adoption, contributing to technology measurement (e.g., Verhoogen, 2023; Cirera et al., 2025).

There is a large literature that examines the rationales and impacts of industrial policy, including recent empirical studies (Juhász, 2018; Bai et al., 2020; Fan and Zou, 2021; de Souza, 2022; Giorcelli and Li, 2021) and quantitative studies (Itskhoki and Moll, 2019; Liu, 2019; Choi et al., 2025b). Relatively few studies integrate theory and data. Exceptions include Lashkaripour and Lugovskyy (2023) and Bartelme et al. (2025), who quantify optimal policies under monopolistic competition and Marshallian externality, 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, but focuses on the big push.

Three recent papers, Kim et al. (2021), Choi and Levchenko (2025), and Lane (2025), study persistent effects of South Korea's HCI Drive 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, Choi and Shim (2024) examine the benefits and costs of technology adoption versus innovation across South Korea's development stages, focusing on the post-1980 period when innovation became more prominent, and Choi et al. (2025a) study firm concentration between 1970-2010. In contrast, this paper focuses on its industrialization in the 1970s.

The paper is also related to the literature on dynamic models of trade, growth, and economic geography (Martin and Ottaviano, 2001; Arkolakis et al., 2019; Peters, 2022; Eckert and Peters, 2023). Our model combines heterogeneous firm models with discrete technology choices (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 market access interacts with the big push.

The rest of this paper is structured as follows. Section 2 describes the background and data. Section 3 presents the empirical findings. Section 4 presents the simple model. Section 5 details quantification. Section 6 presents counterfactual results. Section 7 concludes.

# 2. Historical Background and Data

## 2.1 Big Push Episode in South Korea

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.

One of the central focuses of the policy was the modernization of technology in heavy manufacturing, as emphasized by its slogan "*nation-building through science and technology, and technological self-reliance (과학입국 기술자립).*"[2] Given its large technology gap with the world frontier, the government considered the adoption of foreign technology as the most effective ways to catch up with the frontier, rather than developing its own.[3] 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—as the new government shifted toward more market-oriented liberalization policies.

Adoption contracts were mutually agreed upon by buyers and sellers. While foreign sellers benefited from adoption fees, the contracts stipulated that sellers were responsible for ensuring that Korean firms could produce specific products at a specified quality level by a designated date. There were 1,634 contracts, with 57% originating from Japan and 21% from the US—two of the most technologically advanced economies at the time. Heavy manufacturing sectors accounted for 85% of these contracts, aligning with the policy narrative. The contracts specified only *pure idea* exchanges—with 95% involving transfer of blueprints or provision of training services, while the remaining 5% licensing agreements—but not about capital equipment imports. Capital equipment was either sourced locally or through separate import contracts with other foreign suppliers (Enos and Park, 1988). As part of these agreements, foreign engineers from technology sellers were required to train Korean workers in process design, the construction of new production lines, and the operation of newly installed capital equipment.

[2]However, the policy did not crowd out technology adoption in light manufacturing (Appendix Figure A.2). Adoption in light manufacturing remained stable during this period.

[3]Unlike earlier industrialization in Europe and the US, where domestic invention or innovation played a central role, late-industrializing economies in the post-war period, such as South Korea, relied primarily on adoption to access the technological frontier and to achieve industrialization (Amsden, 1989). The aggregate R&D-to-GDP ratio during our sample period was only 0.46%, substantially lower than the roughly 2% observed in the 2010s when South Korea had reached the frontier, indicating that domestic innovation played a relatively limited role during the policy period (Choi and Shim, 2024).

The government selectively provided firm-specific subsidies to a subset of adoption contracts based on their potential for large economic gains. One of the primary subsidy instruments for technology adoption was firm-specific subsidies allocated through foreign credit (Choi and Levchenko, 2025). The majority of these credits were designated specifically for technology adoption. The directed credit effectively functioned as a subsidy, as government guarantees enabled firms to borrow at significantly lower interest rates than those available from other sources.[4] These credits were used not only to cover adoption fees but also to install capital equipment and extend production lines, both related to newly adopted technologies.

The government also implemented a range of complementary policies to promote heavy manufacturing, such as the construction of industrial complexes, export promotion through international trade fairs organized by the Korea Trade Promotion Agency (KOTRA) (Barteska and Lee, 2023), and input tariff exemptions for exporters (Connolly and Yi, 2015). These policies played a particularly important role in the early phase of the initiative, as reflected in the early rise of the heavy manufacturing sector's GDP share, as shown in Figure 1. While there were also tax credits for fixed adoption fees, they were *not part of the HCI Drive*, had been in place since 1966, and their exemption rates remained unchanged through 1982 (Choe and Lee, 2012). These credits applied *uniformly across all sectors and firms*, rather than being specific to heavy manufacturing.

## 2.2 Data

We construct our main dataset by merging firm-level balance sheets with technology adoption activities. Our dataset covers manufacturing firms from 1970 to 1982, classified into 10 sectors, including 4 heavy manufacturing sectors. Administrative municipalities are aggregated into 86 regions. Appendix B provides details on the data construction. Appendix Table C.1 presents the descriptive statistics.

[4] Due to balance of payments concerns, the government strictly regulated Korean firms from borrowing US dollars through the Foreign Capital Inducement Act.

We manually collected and digitized firm-level data on technology adoption from official adoption contract documents, sourced from the National Archives of Korea, and surveys published by the Korea Industrial Technology Association.[5] These documents contain information about the 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, 1,634 contracts were signed by 587 unique Korean firms.

Firm balance sheet data are digitized from 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 available from 1972). All monetary values are converted into 2015 US dollars. It covers 6,230 unique firms, 47% classified as heavy manufacturing, and covers 70% of national manufacturing gross output. We merge the balance sheet data with the technology adoption data based on firm names. Some observations report missing employment. To better leverage the data, we drop these observations only when employment is required in the analysis, and conduct robustness checks on this issue.

The annual survey also has information on addresses of firms' plants and affiliated business groups (also known as chaebols). Based on the address information, we link their adoption activities to their production locations. We use the business group information to construct the IV for local spillovers and complementarity. There are 59 business groups, with an average of 5 firms per group. They were larger size and more likely to adopt technology, with sizable variation across groups.

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.

[5]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 adoption contracts, with related documents preserved in the National Archives of Korea.

Credit data, one of the main subsidy instruments for adoption, come from Choi and Levchenko (2025), who compiled information on the total foreign credit allocated by the government. Although annual firm-level data on total credit received are available, the portions specifically devoted to technology adoption or to individual contracts are not observed. About 50% of technology adoption contracts between 1973 and 1979 were made by firms that received government credit. Among heavy manufacturing firms that operated during the sample period, 16% adopted at least one technology. Of these adopters, 21% received credit at least once. A small fraction of firms received credit without engaging in any adoption activity. 2% of firms received credit despite never adopting any technologies.

We obtain each firm's total revenues and the number of participations in trade fairs from KOTRA's Annual Reports on International Trade Fairs, import tariffs from Luedde-Neurath (1986), and input-output tables from the Bank of Korea.

# 3. Empirical Evidence

We present three findings on the direct effects on adopters, local spillovers to non-adopters, and local complementarity.

## 3.1 Direct Effects on Adopters

**Winners vs. losers research design.** One of the main econometric challenges in estimating the direct effects is the presence of unobservables that cause selection bias. 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). Winners serve as the treated group, while losers serve as the control group.

Losers are defined as firms that signed contracts that 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 teams, or sudden requests for modifications to contractual terms after the 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.[6] Never-adopters are firms that did not adopt technology at any point following the cancellations. As a result, the cancellations create exogenous variation in the timing and status adoption.

Each loser is matched with up to 3 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, local labor market conditions, and industrial complexes. Second, within region-sectors, we select winners most similar to a loser based on the Mahalanobis distance, with replacement, using four variables: log assets, log fixed assets, and their one-year growth. This results in 38 matches among 106 unique firms. Among these 38 matches, there are 25 not-yet-treated and 13 never-treated losers.

Using the matched sample, 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. Outcomes $y_{imt}$ are log sales or TFPR (see Appendix C.2 for its estimation). $D_{mt}^{\tau}$ are event study dummies: $D_{mt}^{\tau} = \mathbb{1}[t - \tau = t(m)]$,

[6] After the initial cancellations, these delayed losers did not make adoption contracts with the foreign firms that canceled the contract. They made contracts with other firms a few years after the cancellations.

where $t(m)$ is match $m$'s event year. $\mathbb{1}[\text{Winner}_{it}]$ is a winner dummy. We normalize $\beta_{-1}$ to zero. $\delta_{im}$ and $\delta_{mt}$ are match-firm and match-year fixed effects. $\varepsilon_{imt}$ is the error term. Standard errors are two-way clustered at the match and firm levels.

One issue is bias due to heterogeneous treatment effects across cohorts in the staggered diff-in-diff design. To address it, we adopt the stacked-by-event design (Cengiz et al., 2019) and construct the estimation dataset based on rolling control groups. We drop matches once delayed-losers adopt technology later, so that the coefficients are identified based solely on within-match comparisons.

The identifying assumption is that losers and winners were ex-ante similar before the event and that cancellations were uncorrelated with unobservables.[7] We provide evidence that supports this assumption. Covariates are well-balanced and pre-event observations do not predict cancellations (Appendix Tables C.5 and C.6). Raw data show that the average log sales of winners began to increase only after adoption, while those of losers followed their pre-trends (Appendix Figure C.1). Also, despite the small number of losers, their sectoral composition closely mirrors that of total contracts, and losers were balanced not only with winners but also the full sample of adopters, supporting that cancellations were random (Appendix Figure C.2 and Table C.4).

**Threats to identification.** We discuss two potential threats to identification. The first is sorting, where losers might have been matched with less competent foreign firms. To check this, we compare the patenting activities—proxies for foreign firms' competence—of foreign firms that contracted with winners versus losers, using data from the US Patent and Trademark Office. The two groups' patenting activities were balanced (Panel B of Appendix Table C.5). Another concern is the Stable Unit Treatment Value Assumption (SUTVA) due to local spillovers or competition. Positive spillovers from winners to losers would lead to an underestimation of the true impact of the direct effects, making our

[7] Delayed and never-adopters share the same identifying assumption. Never-adopters can be interpreted as firms whose treatment occurred outside the sample period (Borusyak et al., 2024).

estimates conservative lower bounds. Any spillovers originating from other local firms in the same region-sector that are common to both winners and losers are absorbed by the match-year fixed effects. Regarding competition, we would expect to see observable negative changes in the trends of losers after the events, but no such changes are detected in the raw plot of sales. Also, because manufacturing sectors are highly tradable and the spatial unit of analysis is quite granular, local competition is unlikely to significantly violate the SUTVA. Moreover, the match-year fixed effects also absorb contemporaneous region-sector policies (e.g., industrial complex).

[Insert Figure 2 here]

**Estimation results.** Figure 2 reports the results (see Appendix Table C.7 for more details). We find no pretrends. Both winners' sales and TFPR start to increase only after the adoption. The coefficients rise for 4 years before stabilizing, which may reflect the time firms need to fully absorb the newly adopted technologies. 7 years post-adoption, sales and TFPR rise by 61% and 101%, respectively.

A potential concern is that these estimates reflect government support rather than the *pure* effects of adoption. If the government reclaimed subsidies from losers after cancellations, the estimates might reflect the *joint* effects of both adoption and government support. If this were the case, we would expect that losers to experience declines in subsidies or export promotion, but we do not observe such declines (Appendix Table C.7). Also, the estimates remain almost identical when including these two variables as controls (Appendix Table C.10). The results remain robust to alternative matching variables, outcomes, inference methods, and the number of matches (Appendix C.6.1).

## 3.2 Local Spillovers

To examine the local spillovers, we define the region-sector $nj$'s adopter share in $t-2$ as[8]:

$$\text{Share}_{(-i)nj,t-2} = \frac{T_{(-i)nj,t-2}}{N_{(-i)nj,t-2}}. \tag{3.2}$$

$N_{(-i)nj,t-2}$ is the number of firms in $nj$ at $t-2$, excluding firm $i$ to avoid mechanical correlation. $T_{(-i)nj,t-2}$ is the number of adopters in $nj$ at $t-2$, also excluding $i$. The two-year lag accounts for the time needed for local knowledge diffusion.

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

$$\Delta y_{it} = \beta \Delta \text{Share}_{(-i)nj,t-2} + \zeta y_{it_0} + \mathbf{X}'_{injt}\gamma + \delta_n + \delta_j + \sum_g D_g \delta_{jg} + \Delta\varepsilon_{it}, \tag{3.3}$$

where the dependent variable is the change in log sales or TFPR. Time-invariant factors are differenced out. $\delta_n$ and $\delta_j$ are region and sector fixed effects. $\delta_{jg}$ are group-sector fixed effects for affiliated firms ($D_g = 1$), which absorb group-sector factors like within-group spillovers. We include $y_{it_0}$ to capture the mean reversion, whereby larger firms tend to grow more slowly. We also check robustness to omitting it. $\mathbf{X}_{injt}$ are additional controls. Standard errors are two-way clustered by region and business group.

Early coverage is incomplete, and firms are not observed in some years. To expand coverage, we use overlapping long differences for 1972-1979 and 1973-1980, which span the policy period. Because standard errors are clustered at the regional level, this approach is innocuous, and we include dummies for each difference set.

Adopter shares can affect firm performance both through spillovers and by influencing adoption decisions. We restrict the estimation sample to firms that never adopted technol-

[8] We focus on local spillovers for two reasons. First, we can exploit local cross-sectional variation. Second, previous studies show that knowledge spillovers operate at the local level (e.g. Atkin et al., 2022). Consistent with this local spillover, both the heavy manufacturing sector and adoption activities were highly geographically concentrated.

ogy, so the estimates only reflect spillovers. To address potential sorting, we restrict the sample to continuing firms, though entry and exit still affect variation in adopter shares.

**IV strategy.** The OLS estimates may be biased, as region-sector unobservables could affect both firms' adoption decisions and their growth. The direction of the bias is ambiguous. Positive shocks could lead to upward bias, whereas unobserved subsidies provided to less productive firms introduce downward bias. Measurement errors in adopter shares, due to incomplete coverage, are another source of downward bias. Restricting the sample to never-adopters also leads to selection bias.

To address these issues, we construct an IV based on the spatial network of business groups with multiple firms across region-sectors. Although only 5% of firms were affiliated with business groups, these firms were major participants in technology adoption, accounting for 43% of the total contracts.[9] The IV exploits group-level adoption decisions as exogenous shifters for adopter shares in regions where groups initially owned firms. For example, the Samsung group owned six electronics firms—four in Suwon and two in Ulsan, 283 km apart. Suppose Samsung made a group-wide adoption decision, driven by group-level productivity or subsidies. This increases the overall adoption in both locations. These group-level factors are captured by the four affiliates in Suwon but, being outside Ulsan, are unlikely to be correlated with Ulsan's local shocks. They therefore serve as exogenous shifters for adopter shares in Ulsan among non-Samsung firms.

Specifically, the IV is defined as follows:

$$\mathrm{IV}_{inj,t-h} = \Delta Z_{inj,t-h}, \qquad \text{where} \qquad Z_{inj,t-h} = \sum_{\tilde{g} \neq g(i)} D_{\tilde{g}njt_0} \times \frac{T_{\tilde{g}(-n)j,t-h}}{N^{p}_{(-i)nj,t-h}}. \tag{3.4}$$

$T_{\tilde{g}(-n)j,t-h}$ 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

[9] See Appendix Tables C.1 and C.2 for descriptive statistics on firms affiliated with business groups and the sectoral composition of these firms. Moreover, business group affiliation is a strong predictor of adoption, even after controlling for firm size and region-sector-year fixed effects (Appendix Table C.3).

$n$ or within a 100 km radius of region $n$. $D_{\tilde{g}njt_0}$ is a dummy of whether group $\tilde{g}$ had at least one firm in region-sector $nj$ in the initial year $t_0$. We sum $T_{\tilde{g}(-n)j,t-h}$ over business groups that had at least one firm in $nj$ in the initial year and normalize the summation by $N^p_{(-i)nj,t-h}$ (the predicted number of firms in $nj$ in $t-h$).[10] We use the predicted numbers to avoid endogeneity. This normalization prevents regions with a large number of firms from mechanically having larger IV values, making the IV consistent with adopter shares.

The identifying assumption is that firms 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.

**Threats to identification.** Before presenting the results, we briefly discuss three potential threats to identification. First, the expansion of business groups may affect region-sector variables through other channels beyond the spillovers from adoption. To address this, we include changes in their sales shares within region-sectors. 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. Appendix C.5 describes the construction of these variables. This variable helps isolate *variation in the predicted adopter shares* from *variation in business group size* within region-sectors.

Second, business groups' sorting can be an issue. There can be two potential types of sorting. The first type is that they 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 is that persistent unobservable shocks prior to 1972 or 1973 affected their initial location choices. With such persistent shocks, the IV would correlate with firms' past performance before 1972 or 1973, but we find no significant correlations (Appendix Table C.20).

Third, the SUTVA might be violated due to spatial interactions with neighboring

[10] $N^p_{(-i)nj,t-h} \equiv g_{(-n)j} \times N_{(-i)nj,t_0-h}$, where $g_{(-n)j}$ is the national growth of the number of sector $j$ firms, excluding those in $n$. $N_{(-i)nj,t_0-h}$ is the number of firms in $nj$ in $t_0-h$, excluding $i$.

business group firms through input-output linkages, but excluding firms within a 100 km radius in the IV mitigates this concern, as the gravity literature shows that internal trade flows sharply fall with distance (Hillberry and Hummels, 2008).

Finally, we further support the identifying assumption by showing that the IV is uncorrelated with credit and export promotion through trade fairs, which are likely to be positively correlated with unobserved subsidies (Appendix Table C.19). Also, the exclusion restriction could be violated if business-group firms were more responsive to region–sector incentives. However, we view this as unlikely, as the interactions between business-group status and either the industrial-complex dummy or the associated tax incentives are insignificant (Appendix Table C.15).

[Insert Table 1 here]

**Estimation results.** Panel A of Table 1 presents the estimation results with the OLS estimates in column 1 and IV estimates in columns 2-8. The IV is strong (see Appendix Table C.13 for the first-stage). Column 3 presents our preferred specification, which includes the predicted business groups' sales shares. The coefficient is reduced somewhat, as this variable isolates the variation in adopter shares from the variation in the size of business groups. This estimate implies that a 1 percentage point increase in adopter shares leads to 2.7% higher sales. We obtain similar results for TFPR (Appendix Table C.12).

While nearby firms' adoption could intensify competition (Bloom et al., 2013), the positive coefficients indicate that spillover effects outweighed any negative competitive pressures. The limited role of competition is consistent with the high tradability of manufacturing sectors and the fine spatial granularity of our analysis. Although the exact mechanisms of spillovers are not directly identified, case studies in Kim (1997), discussed in Appendix D.4, suggest that learning and labor mobility were key channels, consistent with evidence from previous studies (e.g. Stoyanov and Zubanov, 2012).

The estimates remain stable to additional controls (see Appendix C.4 for details). Column 4 adds internal and international market access (Donaldson and Hornbeck, 2016);

Column 5, directed credit; Column 6, industrial-complex dummies and related tax incentives; Column 7, import and input tariffs and firm-level trade policies (Connolly and Yi, 2015; Barteska and Lee, 2023); and Column 8 includes all controls jointly.

### 3.3 Local Complementarity in Adoption Decisions

To test for local complementarities, we estimate equation (3.3) using the full sample of all firms, regressing new adoption contract dummies on adopter shares. A positive coefficient indicates local complementarity. Panel B of Table 1 reports the results. After correcting for endogeneity, the estimate becomes positive and significant. The IV estimate in column 3, controlling for business groups' sales shares, implies that a 1 percentage point increase in adopter shares raises the probability of new contracts by a 0.85 percentage point—about 14% of the 1979-1980 average (6%). Columns 4–8 add the same additional controls as in the spillover regression, and the coefficients remain stable.[11]

We also examine heterogeneity in market size by interacting adopter shares with indicators for regions above and below the 80th percentile of initial market access. The coefficients, 1.07 and 0.29, differ significantly at the 10% level (Appendix Table C.16). The results are robust to alternative cutoffs. These results suggest that market access amplifies local complementarity, which will be embedded in our quantitative analysis.

To summarize, although the 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. Local spillovers point to potential positive externalities, suggesting that private returns alone may not have been sufficient to overcome coordination failures. If these failures resulted in multiplicity, the temporary big push could have shifted the economy to a higher-adoption state, where firms likely continued adopting even after subsidies ended, driving South Korea's industrialization

[11] Firms were more likely to adopt technologies from countries previously chosen by local peers, consistent with information frictions and supporting the interpretation of coordination failures (Appendix Table C.17).

# 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, $t \in \{1, 2, \ldots\}$. Labor endowment is exogenously given as $L$. There is a fixed mass of monopolistically competitive firms, indexed by $i$, with total mass normalized to 1. Each firm produces a unique variety. These varieties are aggregated through a CES aggregator to produce final consumption goods. Representative households inelastically supply labor and earn a wage $w_t$.

**Firm.** Firm production function is linear in labor: $y_{it} = z_{it} l_{it}$, where $l_{it}$ is labor input, and $z_{it}$ is productivity. 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, $\sigma > 1$ is the elasticity of substitution, $Q_t = \left(\int q_{it}^{\frac{\sigma-1}{\sigma}} \mathrm{d}i\right)^{\frac{\sigma}{\sigma-1}}$ is the aggregate quantity, and $P_t = (\int p_{it}^{1-\sigma} \mathrm{d}i)^{\frac{1}{1-\sigma}}$ is the price index. Firms optimally charge constant markups $\mu = \frac{\sigma}{\sigma-1}$ over their unit costs $p_{it} = \frac{\mu w_t}{z_{it}}$.

Firms are heterogeneous in productivity. Their decisions to adopt modern technology, along with spillovers from adoption, endogenously determine their productivity in equilibrium. Firm productivity is composed of three components:

$$z_{it} \equiv z_{it}(T_{it}, \lambda_{t-1}^{T}) = \eta^{T_{it}} \times f(\lambda_{t-1}^{T}) \times \phi_{it}, \qquad f(\lambda_{t-1}^{T}) = \exp\left(\delta \lambda_{t-1}^{T}\right). \tag{4.1}$$

$\eta^{T_{it}}$ governs direct productivity gains from adoption, where $\eta > 1$ and $T_{it}$ is a binary adoption status. $f(\lambda_{t-1}^{T})$ is adoption spillovers that increase with the previous period share $\lambda_{t-1}^{T}$, with $\delta$ governing the strength of spillovers. We set spillovers to operate with a one-period lag, which reflects the time needed for local diffusion of knowledge. This functional form and the lag align with the spillover regression. Appendix D.4 provides two microfoundations for spillovers, based on labor mobility and learning. $\phi_{it}$ is firm-specific exogenous productivity, iid across firms and periods.

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

$$\pi_{it} = \max_{T_{it}\in\{0,1\}} \left\{ \frac{1}{\sigma}\left(\frac{\mu w_t}{z_{it}(T_{it}, \lambda^T_{t-1})}\right)^{1-\sigma} P_t^\sigma Q_t - T_{it} P_t F^T \right\}. \tag{4.2}$$

Firms internalize their direct gains but take positive spillovers as given. This positive externality leads to adoption rates below the social optimum.

**Equilibrium.** In each period, given $\lambda^T_{t-1}$, firms make adoption decisions to maximize profits, and goods and factor markets clear (static equilibrium). The adopter share $\lambda^T_t$ is a state variable that evolves based on the adoption decisions (dynamic equilibrium). Given $\lambda^T_{t-1}$, $\lambda^T_t$ is determined in period $t$, and so on.

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

Only firms with $\phi_{it}$ above the cutoff $\bar{\phi}^T_t$ adopt. Under the Pareto distribution, the cutoff becomes $\bar{\phi}^T_t = (\lambda^T_t)^{-\frac{1}{\theta}}$. The equilibrium adopter share in each period 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

$$\hat{\lambda}^T_t = \left[ A(\hat{\lambda}^T_t)^{2-\sigma} \frac{(\eta^{\sigma-1}-1)}{\sigma F^T} f(\lambda^T_{t-1}) L \right]^{\frac{\theta}{\sigma-1}},$$
$$\text{where} \quad A(\lambda^T) = \left[ \frac{\theta}{\theta-(\sigma-1)} \left( (\eta^{\sigma-1}-1)(\lambda^T)^{\frac{\theta-(\sigma-1)}{\theta}} + 1 \right) \right]^{\frac{1}{\sigma-1}}. \tag{4.4}$$

The time-invariant steady state adopter shares 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 $\sigma$ weakens the competition effect and strengthens the cost-reduction effect, generating complementarity and the potential for static multiple equilibria within each period.[12] However, by imposing $\sigma > 2$, the competition effect remains sufficiently strong, ruling out this possibility and ensuring a unique static equilibrium. Moreover, $\lambda_t^T$ increases with $\eta$ and $\delta$, as they boost private returns and spillovers from adoption.

Because of the unique static equilibrium in each period, given any initial adopter share $\lambda_{t_0}$, there exists a unique sequence of static equilibria that forms a deterministic dynamic path from $\lambda_{t_0}$ to a steady state. This path exhibits dynamic complementarity in adoption, meaning $\lambda_t^T$ increases with $\lambda_{t-1}^T$, 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 adoption costs $P_t F^T$, further encouraging adoption. If either condition is not met, the complementarity does not emerge. If adoption costs are in units of labor, the complementarity fails to arise, regardless of the strength of spillovers, because spillovers also raise wages through increased labor demand, exactly offsetting the gains. Thus, adoption costs in units of final goods are essential to reproduce the third empirical finding, as spillovers alone cannot reproduce this outcome (see Appendix D.3 for more details). Importantly, multiple steady states can arise from dynamic complementarity, and the initial adopter share determines which steady state will be realized, implying path dependence. Also, they can be Pareto-ranked based on adopter shares. Proposition 1 summarizes these results.

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

[12] 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).

*(i) (Uniqueness) Given any initial adopter share $\lambda_{t_0}^T$, there exists a unique 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) Multiple steady states can be Pareto-ranked based on adopter shares.*

The case of multiple steady states is illustrated in Panel A of Figure 3. The red locus, defined by equation (4.3), represents short-run equilibrium adopter shares $\lambda_t^T$ conditional on the previous period's $\lambda_{t-1}^T$. The equilibrium moves along the red locus as time passes. Steady states are determined at points where $\lambda_{t-1}^T = \lambda_t^T$ for all $t$, where the red locus intersects the 45-degree blue line. In this case, there are three intersection points ($S^{\text{Pre}}$, $S^{\text{U}}$, and $S^{\text{Ind}}$), corresponding to the pre-industrialized, unstable, and industrialized steady states, respectively. $S^{\text{U}}$ is unstable, so it is excluded from our focus.

[Insert Figure 3 here]

An initial adopter share $\lambda_{t_0}^T$ determines the long-run steady state. If $\lambda_{t_0}^T \in [0, S^{\text{U}})$, the economy converges to $S^{\text{Pre}}$. If $\lambda_{t_0}^T \in (S^{\text{U}}, 1]$, it converges to $S^{\text{Ind}}$. These steady states can be Pareto-ranked based on their adopter shares, with $S^{\text{Ind}}$ 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 ($\delta = 0$), $\lambda_t^T$ becomes independent of the previous share, leading to a unique steady state, indicated by the single intersection of the green dashed horizontal and 45-degree lines.

The two key parameters, $\delta$ and $\eta$, are preconditions for the big push (Proposition 1(iv)). Multiple steady states 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 $\delta$ (or $\eta$) 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.

If an initial condition is trapped in the *underdevelopment* region $[0, S^{U})$, a big push that provides a temporary subsidy for adopters' inputs or adoption costs can have permanent effects by moving the economy to the industrialized steady state (Panel C). 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 firm scale.

**Proposition 2.** *Suppose the multiple steady states exist and the economy is initially in the underdevelopment region, $\lambda^{T}_{t_0} \in [0, S^{U})$:*
*(i) (Big push) There exists a threshold $\underline{s}$ such that a one-time subsidy for adopters' inputs 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 for the quantitative analysis. Additional details are provided in Appendix E. The world is divided into Home and Foreign. Home is a small open economy taking Foreign aggregates as given. Home consists of multiple regions, $n, m \in \{1, \ldots, N\} \equiv \mathcal{N}$, and sectors, $j, k \in \{1, \ldots, J\} \equiv \mathcal{J}$. Each sector's varieties are tradable across both regions and countries, subject to import tariffs $t_{jt}$ and internal and international iceberg costs $d_{nmj}, d^{x}_{nj} \geq 1$. In each region, immobile representative households supply labor inelastically in a competitive labor market.

In each region-sector, there is a fixed mass of monopolistically competitive firms, $M_{nj}$. A CES aggregator combines Home and Foreign varieties into nontradable local aggregates for consumption and intermediate inputs. Home firms face Foreign demand schedule $p^{-\sigma}_{it} D^{x}_{jt}$, where $D^{x}_{jt}$ is exogenous Foreign demand. Exporters incur fixed export costs $F^{x}_{j}$ in units of labor, implying that $F_j^x$ does not exhibit the dynamic complementarity.

Firm production function is constant return to scale Cobb-Douglas: $y_{it} = z_{it} L_{it}^{\gamma_j^L} \prod_k (M_{it}^k)^{\gamma_j^k}$. $L_{it}$ and $M_{it}^k$ are labor and sector $k$ intermediate inputs. Productivity $z_{it}$ consists of three terms as in the simple model: $z_{it} = \eta^{T_{it}} f(\lambda_{nj,t-1}^T)\phi_{it}$. The spillovers operate at the region-sector level. $\phi_{it}$ is iid and distributed as a bounded Pareto distribution: $\phi_{it} \sim \frac{1-(\phi_{it}/\phi_{njt}^{\min})^{-\theta}}{1-\kappa^{-\theta}}$, parametrized by $\phi_{njt}^{\min}$, $\kappa$, and $\theta$.[13] The lower bound of the distribution, $\phi_{njt}^{\min}$, varies across regions, sectors, and periods, while the upper bound, $\kappa\phi_{njt}^{\min}$, is proportional to the lower bound by $\kappa$. This rationalizes regions with zero adoption: if the cutoff exceeds $\kappa\phi_{njt}^{\min}$, no firms adopt. The Pareto assumption yields closed-form expressions for region-sector aggregates, enabling us to solve the model at the region-sector rather than firm level.

Firms are subject to idiosyncratic output distortions (or taxes): $\tau_{it} = \bar{\tau}_j z_{it}^{\xi_j}$ (Hsieh and Klenow, 2009). $\bar{\tau}_j$ and $\xi_j$ govern the average level of distortions and their relationship with productivity, respectively, with a negative $\xi_j$ implying relatively higher taxes on more productive firms. Tax revenues from these distortions are rebated back to households.

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.[14] We assign Cobb-Douglas shares 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 the unit cost of input bundles: $c_{njt} \propto (w_{nt})^{\gamma_j^L} \prod_k (P_{njt})^{\gamma_j^k}$.

We model adoption subsidies as input subsidies $0 \le s_{njt} \le 1$, varying across regions, sectors, and periods. They are financed by a common labor tax $\tau_t^w$ with a balanced budget.

[13] With fixed adoption costs, persistence in firm productivity does not affect our results. For example, if the firm-specific component is Pareto-distributed but time-invariant (i.e., perfectly persistent), we still obtain closed-form region-sector aggregates and the calibration remains unchanged. However, with sunk costs, adoption would be forward-looking and the persistence becomes central (e.g. Jaimovich et al., 2023): with weak persistence, current productivity provides little information about future profitability, making sunk costs rarely worthwhile. Because persistence combined with sunk costs generates hysteresis, the big push may be amplified with sunk costs. We further discuss this in Appendix E.1.

[14] These costs capture various types of fixed expenses associated with adoption, such as plant installation and the uniform tax credits that had been in place since 1966 and remained unchanged through 1982.

With these subsidies, adopters' unit costs of production become $\frac{(1-s_{njt})c_{njt}}{z_{it}}$.

Households have Cobb-Douglas preferences with shares $\alpha_j$. 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 them in proportion to their labor incomes.

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 $\{\lambda^T_{njt}\}$.

The extended model incorporates other contemporaneous policies and financial frictions arising from limited financial development (Buera and Shin, 2013). $\phi^{\min}_{njt}$ captures productivity shifters not explained by adoption, such as the construction of industrial complexes. $D^x_{jt}$ reflects changes in foreign demand or government export promotion. Output distortions map one-to-one to input distortions that rationalize the same firm size distribution when labor is the only factor of production. They can be microfounded by working-capital constraints, which capture financial frictions in reduced form.

## 5.2 Taking the Model to the Data

Each period in the model corresponds to 4 years. Sectors are classified into four broad groups: commodity, light and heavy manufacturing, and service. Because adoption mostly occurred in heavy manufacturing, we assume that adoption is only available within this sector. We calibrate the model to the years 1972, 1976, and 1980 ($t = 1, 2, 3$). After $t = 3$, fundamentals are held constant at the 1980 levels. We hold them constant to focus on the intervention period and abstract from subsequent shifts beyond the model's scope, effectively detrending post-1980 growth. Given the initial adopter shares and population taken directly from the data, we solve the model for $t = 1$ and then proceed period by period until it converges to a steady state.

Adoption subsidies are provided in periods $t = 2, 3$ to firms located in regions with at least one recipient of directed credit, denoted $\mathcal{N}^{s}$ (35 out of 86 regions). We assume a uniform subsidy rate $\bar{s}$ across these regions and periods, such that $s_{njt} = \bar{s}$ for all $n \in \mathcal{N}^{s}$ and $t \in 2, 3$, and $s_{njt} = 0$ otherwise.

We calibrate subsidies $\bar{s}$, tariffs $t_{jt}$, fundamentals $\mathbf{\Psi}_t$, and sets of structural parameters: $\mathbf{\Theta}^{\mathrm{E}} = \{\eta, \delta,\ M_{nj},\ \theta,\ \sigma,\ \xi_j,\ \gamma_j^L,\ \gamma_j^k,\ d_{nmj},\ d_{nj}^x,\ \alpha_j\}$ and $\mathbf{\Theta}^{\mathrm{M}} = \{\kappa, F_j^x, F^T, \bar{\tau}_j\}$. $\mathbf{\Theta}^{\mathrm{E}}$ and $t_{jt}$ are externally calibrated. $\bar{s}$, $\mathbf{\Psi}_t$, and $\mathbf{\Theta}^{\mathrm{M}}$ are internally calibrated via the method of moments. Because we solve the entire model when calibrating, our calibration incorporates the impacts of input-output linkages and spatial interactions on adoption. Table 2 summarizes our calibration procedure with estimation results, with details in Appendix F.2.

[Insert Table 2 here]

**External calibration.** We set $\sigma$ to 5 following Peters (2022). By taking the log of adopter sales, 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 $\delta_{mt}$ absorb out variables common within region-sectors (i.e., local spillovers, unit costs, and market size). From this mapping, we set $\eta = \exp\left(\frac{0.9}{\sigma-1}\right) = 1.25$, where 0.9 is obtained from the average coefficient 7 years after adoption across specifications (Appendix Tables C.7 and C.9).

For non-adopters, taking the log of sales gives: $\ln \mathrm{Sale}_{it} = (\sigma - 1)\delta\lambda_{njt}^{T} + \mathbf{X}_{njt}'\gamma + (\sigma - 1)\ln \phi_{it}$, which can be mapped to the spillover regression. $\mathbf{X}_{njt}$ includes region-sector variables, such as unit cost and market access terms. This relationship pins down $\delta$ to be $2.7/(\sigma - 1) = 0.68$, where 2.7 is the average of the IV estimates from Panel A of Table 1.

Import tariffs are taken from the data. Iceberg costs are parameterized as $d_{nmj} = (\mathrm{Dist}_{nm})^{\upsilon_j}$ and $d_{nj}^x = (\mathrm{Dist}_n^{\mathrm{port}})^{\upsilon_j}$, where $\mathrm{Dist}_{nm}$ is the interregional distance and $\mathrm{Dist}_n^{\mathrm{port}}$ is the distance to the nearest port. Distances between regions connected by the Gyeongbu Expressway are reduced by 66%, consistent with government reports. Fastest routes are computed using the Dijkstra algorithm. We set $(\sigma - 1)\upsilon_j = 1.29$ for commodities and manufacturing, and 3.8 for services (Monte et al., 2018; Gervais and Jensen, 2019).

We set $\theta = 1.06 \times (\sigma - 1)$ (di Giovanni et al., 2011). Given values of $\sigma$ and $\theta$, we infer $\xi_j$ from the firm size distribution following Buera et al. (2021) (see Appendix F.1 for details). Under the Pareto distribution, $\frac{\theta}{\sigma(1+\xi_j)-1} = -\frac{\partial \log\left(1-H_{njt}(\text{Sale})\right)}{\partial \log \text{Sale}_{it}}$ holds among non-exporters within region-sectors, where $H(\cdot)$ is the cumulative distribution of sales. This yields $\xi_j = -0.30$ for heavy manufacturing, implying that more productive firms face higher distortions.[15] To focus on heavy manufacturing, we assume that other sectors do not feature distortions (i.e., $\bar{\tau}_j = 0$).

$M_{nj}$ 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 $\phi_{njt}^{\min}$ under fixed entry. The Cobb-Douglas shares ($\alpha_j$, $\gamma_j^k$, and $\gamma_j^L$) are taken from the input-output tables.

**Internal calibration.** We calibrate $\mathbf{\Theta}^{\mathrm{M}}$, $\bar{s}$, and $\mathbf{\Psi}_t$ by minimizing the distance between the model $\mathbf{m}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)$ and data moments $\mathbf{m}$ subject to the constraints, which impose that the model variables $\mathbf{C}(\mathbf{\Theta}^{\mathrm{M}}, \bar{s}, \mathbf{\Psi}_t)$ match the corresponding data variables $\mathbf{C}$:

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

The moments are normalized to express their differences as percentages.

We calibrate these 6 parameters to match 7 targeted moments 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 $\eta$ and $\delta$, increases in adopter shares in 1976 and 1980 relative to the 1972 level indicate the effects of subsidies, as $\bar{s}$ is only applied to these two periods.[16] The share of regions with zero adoption identifies $\kappa$, as lower $\kappa$ increases the likelihood that the adoption cutoff

[15] This estimate of $-0.3$ lies within the range reported in the literature, from $-0.2$ in Buera et al. (2021) to $-0.5$ in Hsieh and Klenow (2009).

[16] Because region-sector productivity and foreign demand are allowed to adjust over time, the effects of export promotion and industrial complex on firm adoption are indirectly captured through these macro moments in the constraints. The micro moment of firm adopter shares identifies $\bar{s}$.

exceeds the Pareto upper bound. We calibrate the export fixed costs $F_j^x$ for the light and heavy manufacturing sectors using the average exporter shares. Since no firm-level data are available for commodity, we set its $F_j^x$ equal to that of light manufacturing. Finally, we target the average distortion level $\bar{\tau}_j$ for heavy manufacturing to match the average corporate statutory tax rate in 1972.

Conditional on $\mathbf{\Theta}^{\mathrm{M}}$ and $\bar{s}$, the fundamentals $\mathbf{\Psi}_t$ are identified by the imposed constraints that match export intensities, import shares, gross output, producer price indices (PPI) growth, and real GDP growth for the years 1972, 1976, and 1980.

**Estimation results.** The model moments closely match their data counterparts. The calibrated subsidy rate implies that subsidies amount to 6% of adopters' input expenditures, corresponding to roughly 0.6% of GDP in total spending.[17] On average, adoption costs are 89 times larger than fixed export costs. We present two non-targeted moments. First, the model captures a positive relationship between adopter shares and market access and a negative relationship between adopter shares and the distance to the port (Appendix Figure F.1). They align with the stronger complementarity with larger market access in our third finding. Second, the model captures positive relationships between regional adopter shares and employment, exports, and exporter shares (Appendix Table F.2).

# 6. Quantitative Results

How would the economy have evolved differently without the big push? We construct a counterfactual economy without the big push by setting $s_{njt} = 0$, and compare it with the baseline scenario with the big push.

[Insert Figure 4 here]

[17]Based on a rough calculation, the 0.6% estimate is consistent with credit data. Firms' total savings on interest payments from government-guaranteed credit, relative to borrowing from domestic banks, amount to about 0.7% of 1972 GDP (see Appendix F.3 for details).

Figure 4 displays the time paths of heavy manufacturing's GDP shares, export intensities, and employment shares for the baseline and the counterfactual. Panel A of Table 3 reports the steady-state differences in these variables. The counterfactual economy converges to a less-industrialized steady state, with the GDP share decreasing by 27% (3.59 percentage points) and the export intensity by 39% (7.75 percentage points) compared to the baseline. In the counterfactual, the GDP share rises only modestly due to evolving fundamentals and input-output linkages, whereas the big push generates a much sharper increase. The economy reaches its steady state roughly 24 years after 1980. Although consumers and firms allocate constant expenditure shares across sectors under Cobb-Douglas preferences and technology, adoption shifts comparative advantage toward heavy manufacturing in a small open economy, raising its export and GDP shares.

While the GDP shares and export intensity rose steadily over time, the employment shares grew faster until 1984 and then declined. This occurred because intensified competition led to greater spatial concentration of heavy manufacturing and reduced its employment in shrinking regions. This concentration led to substantial heterogeneity across regions. Steady-state regional differences in GDP shares ranged from −15.4% to 77.3% (Panel C). This heterogeneity suggests that aggregate industrialization was driven by localized productivity improvement, rather than by uniform growth nationwide, with only four regions exhibiting higher GDP shares in the baseline (Appendix Figure F.2).

[Insert Table 3 here]

We compute each region's consumption-equivalent welfare and aggregate welfare as their population-weighted average, with a discount factor of 0.85. The big push increased aggregate welfare by 14.6%, but with regional welfare effects ranging from −1.2% to 83.8%. These distributional effects reflect two opposing forces from localized productivity improvements. While households and firms in other regions benefited from lower prices via internal trade linkages, intensified competition reduced their profits.

The big push raised aggregate output relative to the counterfactual, except for the commodity sector (Panel B). Light manufacturing and services, though not directly targeted by the policy, benefited through input-output linkages. However, the commodity sector relied less on heavy-manufacturing inputs and therefore experienced weaker linkage effects, and the increased wage pressure from higher labor demand further reduced its output. Total output, a gross-output-weighted average, was 21% higher.[18]

Next, we examine how factors that reduce firm scale weaken the big push. These factors are temporarily adjusted only during the policy period, with post-1980 levels held constant to focus on their interaction with the big push (Panel C). Between 1972 and 1980, foreign demand rose by 48% relative to domestic demand—which can be driven by, for example, government-led export promotion, increased world demand, and reduced trade costs. Holding it at the 1972 level reduces the steady-state heavy manufacturing GDP share (col. 1). Similarly, keeping import tariffs at their 1972 level (38.4%) instead of allowing the observed 40% decline raises production and adoption costs, offsetting gains from reduced competition (col. 2). Reversing the 66% reduction in travel times from highway construction also weakens the effects (col. 3). Shutting down internal trade within heavy manufacturing eliminates the big push entirely (col. 4). Finally, we worsen misallocation by taxing more productive firms, implemented by reducing $\xi_j$ by 10% or increasing $\bar{\tau}_j$ by 10%. These exercises make more productive firms' scale relatively smaller or make the overall firm scale smaller, which also weakens the effects (cols. 5-6).

Overall, these exercises suggest that coordinated policies were important for the big push to succeed. Without export promotion, highway construction, or under a protectionist scheme similar to Latin America's Import Substitution Industrialization era, firms would have remained too small to adopt new technologies, weakening the big push. Also, financial reforms that improve resource allocation could amplify its effect.

[18] While the 21% increase is larger than the 14% rise in aggregate welfare, this difference arises because Cobb-Douglas input-output linkages vary over time, and total output is measured using gross output weighted by initial gross output, whereas consumption is based on value added weighted by population.

Appendix F.4 presents additional exercises on alternative policy schemes and robustness checks. General subsidies provided regardless of adoption status yield weaker effects, whereas the optimal subsidy moves the economy to a steady state with higher heavy manufacturing GDP shares. Randomized subsidy allocations show that only market access predicts stronger big-push effects. For robustness, we also extend the model to incorporate household spatial mobility and conduct sensitivity analyses on key parameters.

# 7. Conclusion

Our study highlights the importance of addressing coordination failures to facilitate the diffusion of advanced technologies in developing economies for sustainable industrial growth. It also suggests the importance of complementary policies that expand market access and reduce resource misallocation for a successful big push.

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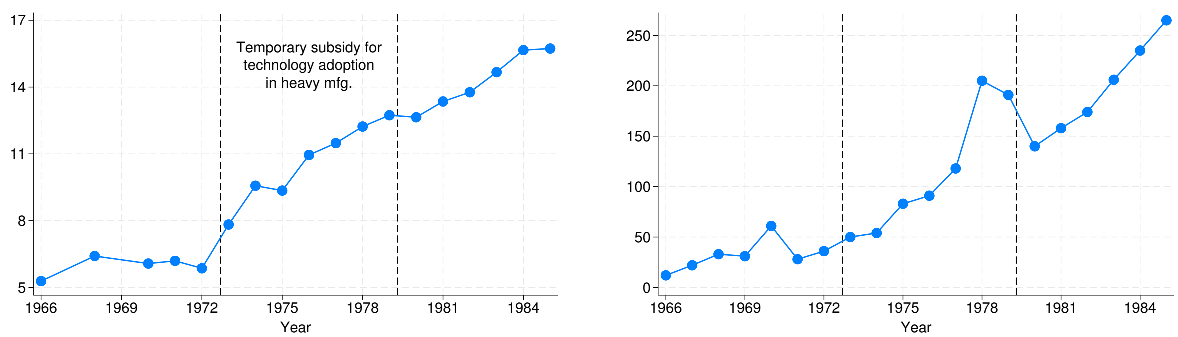
Figure 1: Big Push, Adoption of Modern Technology, and Industrialization in South Korea

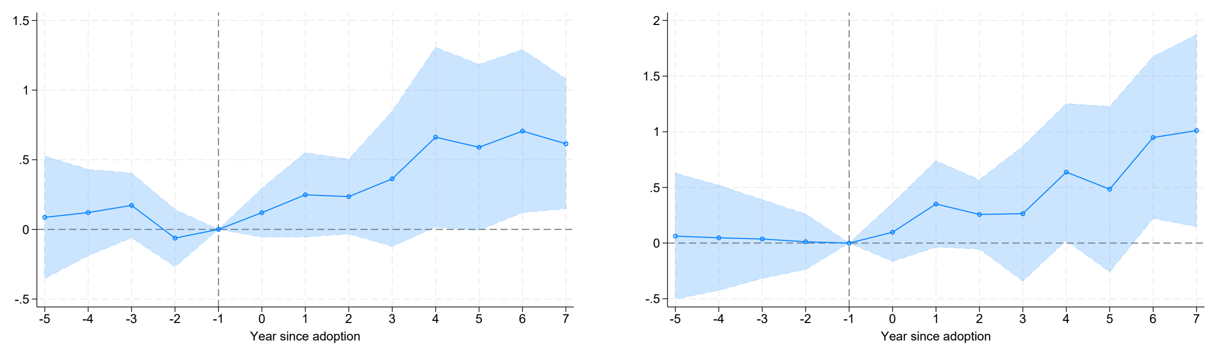



A. Heavy mfg. share of GDP (%)

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

***Notes.*** The vertical lines indicate the start and end of the South Korea's big push. Appendix Figure A.1 shows similar patterns for employment and exports.

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




A. Log sales B. TFPR

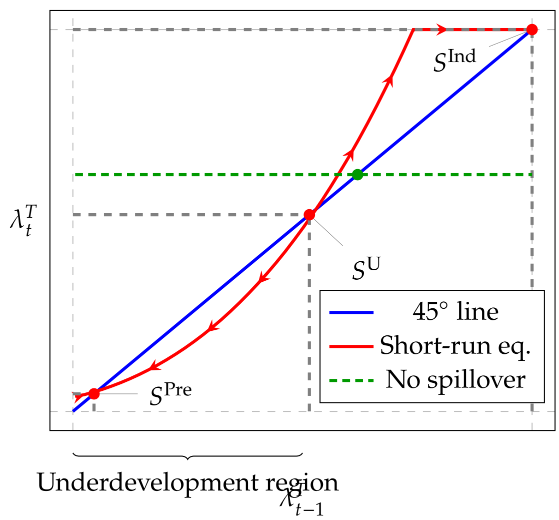
***Notes.*** This figure presents the estimated $\beta_\tau$ in eq. (3.1). The dotted lines represent the 95% confidence intervals based on standard errors that are two-way clustered at the match and firm levels.

Table 1: Local Spillover and Complementarity

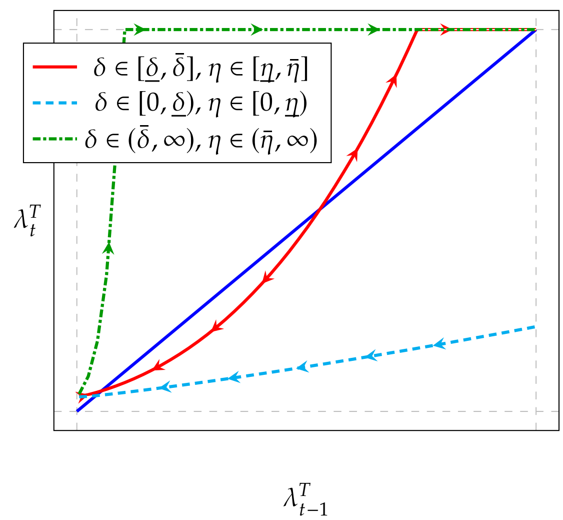
| | OLS | IV | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Panel A. Local Spillover** | Dep. $\Delta \ln \text{Sale}_{it}$ 1972-1979 or 1973-1980 | | | | | | | |
| $\Delta\text{Share}_{(-i)nj,t-2}$ | 0.37 | 3.19*** | 2.70*** | 2.45*** | 2.62*** | 2.67*** | 3.02*** | 2.83*** |
| | (0.42) | (0.74) | (0.73) | (0.77) | (0.74) | (0.73) | (0.78) | (0.82) |
| KP-$F$ | | 17.84 | 21.56 | 17.85 | 21.50 | 20.33 | 22.47 | 16.43 |
| # Clusters | 79 × 1,294 | | | | | | | |
| N | 1,492 | 1,492 | 1,492 | 1,492 | 1,492 | 1,492 | 1,492 | 1,492 |
| **Panel B. Local Complementarity** | Dep. $\Delta\mathbb{1}[\text{New Contract}_{it}]$ 1972-1979 or 1973-1980 | | | | | | | |
| $\Delta\text{Share}_{(-i)nj,t-2}$ | −0.08 | 0.79** | 0.85** | 0.82* | 0.85** | 0.90** | 0.82** | 0.84** |
| | (0.11) | (0.36) | (0.41) | (0.42) | (0.42) | (0.41) | (0.39) | (0.39) |
| KP-$F$ | | 13.92 | 17.72 | 17.53 | 17.81 | 17.16 | 19.06 | 18.29 |
| # clusters | 86 × 1,548 | | | | | | | |
| N | 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 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 eq. (3.3). Adopter shares and IVs are defined in eqs. (3.2) and (3.4). In Panel A, the number of observations is smaller because the sample consists of firms that never adopted technology between 1970-1982. In Panels A and B, the dependent variables are changes in log sales and dummies of making new contracts (1972-1979/1973-1980), respectively. Columns 3-8 include business groups' predicted sales shares (eq. (C.4); see Appendix C.5). Column 4 includes predicted market access (eq. (C.2)) and log distance to port interacted with predicted exports. Column 5 includes the inverse hyperbolic sine of cumulative credit received (1972-1979/1973-1980). Column 6 includes industrial complex dummies and associated tax favors. Column 7 includes changes in log import/input tariffs, interacted with log distance to port and initial export status, and the inverse hyperbolic sine of total revenues and the number of participation in international trade fairs (1972-1979/1973-1980). 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.

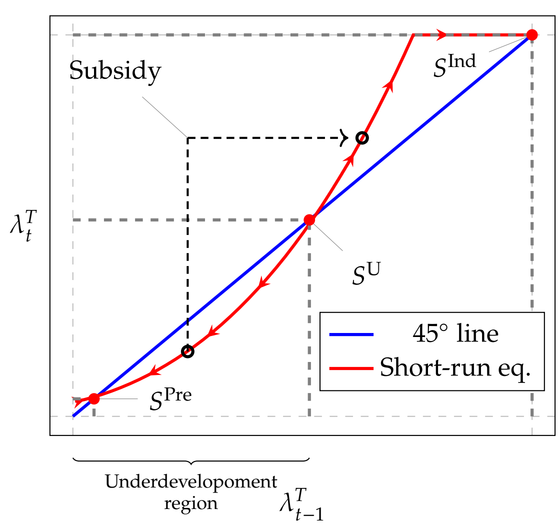
Figure 3: Multiple Steady States and the Big Push



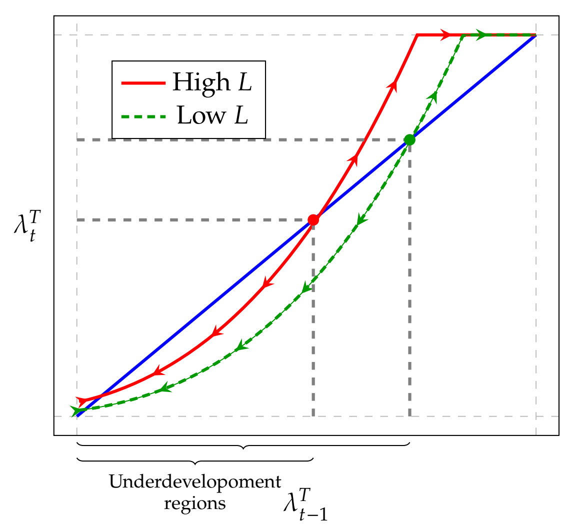

Panel A. Multiple steady states




Panel B. Comparative statics $\delta$ and $\eta$




Panel C. Big push

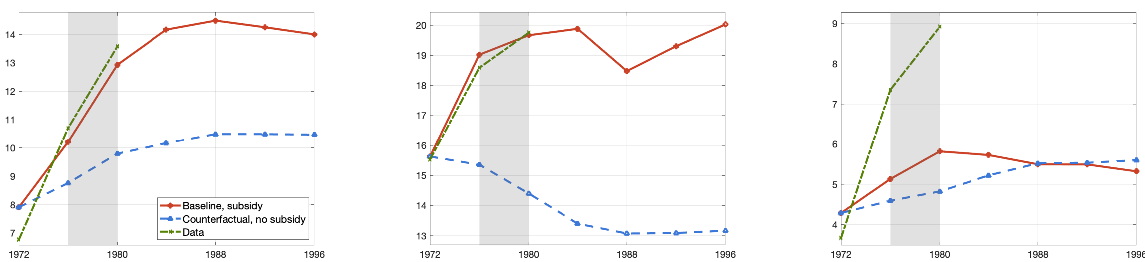



Panel D. Market size

Table 2: Calibration Summary

| | Description | Value | Identification / Moments | Model fit | Data |
|---|---|---|---|---|---|
| | | | *External calibration* | | |
| $\eta$ | Direct productivity gains | 1.25 | Winners vs. losers (pooled), App. Table C.7 & C.9 | | |
| $\delta$ | Spillover semi-elasticity | 0.68 | Spillover estimate, Table 1 | | |
| $\sigma$ | Elasticity of substitution | 5 | Peters (2022) | | |
| $\theta$ | Pareto shape parameter | 4.24 | di Giovanni et al. (2011) | | |
| $\xi_j$ | Distortion corr. | 0.30 | Firm distribution | | |
| $\xi$ | Distance trade cost elasticity | 0.32, 0.95 | Monte et al. (2018), Gervais and Jensen (2019) | | |
| $\alpha_j$ | Preferences | 0.05–0.47 | IO table | | |
| $\gamma_j^k$ | 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 | 0.06 | 0.07 |
| $F_j^x$ | Fixed export cost, light mfg. | 0.11 | Exporter share, light mfg. | 0.35 | 0.34 |
| $F_j^x$ | Fixed export cost, heavy mfg. | 0.011 | Exporter share, heavy mfg. | 0.21 | 0.19 |
| $\bar{s}$ | Subsidy rate | 0.06 | Avg. adopter shares, 76 | 0.11 | 0.09 |
| | | | Avg. adopter shares, 80 | 0.09 | 0.15 |
| $\kappa$ | Pareto upper bound | 1.40 | Share of regions with adoption | 0.53 | 0.47 |
| $\bar{\tau}_j$ | Distortion lev. | 0.975 | Corporate statutory tax rate, 72 | 0.20 | 0.20 |

Figure 4: Aggregate Effects of the Big Push. Baseline vs. Counterfactual




A. HCI GDP share (%) B. HCI export intensity (%) C. HCI emp share (%)

***Notes.*** The green solid line represents the data. The red dotted and blue dashed lines represent the baseline and counterfactual economies. The gray-shaded areas represent the policy periods.

Table 3: Aggregate and Local Effects of the Big Push. Baseline vs. Counterfactual

| **Panel A.** | Steady state differences (Baseline − counterfactual) | | | |
|---|---|---|---|---|
| | $\Delta$GDP share (p.p) | $\Delta$Export intensity (p.p) | $\Delta$Emp share (p.p) | $\Delta$Welfare (%) |
| Aggregate change | 3.59 | 7.75 | -0.13 | 14.61 |
| Local range | $[-15.38, 77.33]$ | $[-1.62, 11.13]$ | $[-15.28, 81.22]$ | $[-1.20, 83.76]$ |

| **Panel B.** | $\Delta$Aggregate Output by Sector (%) | | | |
|---|---|---|---|---|
| Commodity | Light mfg. | HCI mfg | Service | Total |
| −2.25 | 5.56 | 64.57 | 8.97 | 21.02 |

| **Panel C.** | Alternative Scenarios: $\Delta$ Heavy mfg. GDP shares (p.p) | | | | |
|---|---|---|---|---|---|
| Lower foreign | Higher import | No highway | No internal | Worsened distortion | |
| demand ($D^x_{\text{heavy},t}$ $\downarrow$) | tariffs ($t_{\text{heavy},t}$ $\uparrow$) | ($d_{nmj}$ $\uparrow$) | trade ($d_{nmj}$ $\uparrow$) | corr. ($\xi_{\text{heavy}}$ $\downarrow$) | level ($\bar{\tau}_{\text{heavy}}$ $\downarrow$) |
| 3.41 | 3.06 | 2.46 | 0 | 1.86 | 1.60 |

***Notes.*** The first row of Panel A reports steady state differences in the aggregate heavy manufacturing sector's GDP shares, export intensities, and employment shares, and welfare changes between the baseline and counterfactual economies. The second row reports ranges of these differences and welfare changes at the local level. Panel B reports aggregate output by sector. Total output is calculated as the gross-output-weighted average of sectoral changes. Panel C presents the results of quantitative exercises where various factors are temporarily adjusted in 1976 and 1980, while their post-1980 levels remain unchanged.