International Spillovers of China's High-Tech Industrial Policies: Evidence from Germany*

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Abstract

This paper offers new evidence on the international spillovers of China's high-tech industrial policies through trade channels between 1996 and 2017. Using newly assembled data from policy documents on the *national prioritized high-tech industries*, I exploit the staggered policy rollout at the granular product level to identify its causal effects on China's export growth, China–Germany trade flows, and related German industries and workers. I reveal that the policies significantly promoted China's exports of targeted high-tech products to Germany and the rest of the world. Yet China also relied on imports of policy-targeted final capital equipment from Germany due to limited domestic substitutes. Using industry-level variation in exposure to policies through input–output linkages, I show that German upstream industries benefited from a positive demand shock from China and experienced employment and wage growth. Although German downstream industries increased imports from China, I find no evidence of negative impacts on their overall employment and wages. The findings suggest that domestic industrial policies, in some cases, can generate large spillover effects on foreign countries through international trade and input–output linkages.

JEL classification: F14, L5, O14, O25

Keywords: industrial policy, high-tech manufacturing, spillovers, input-output linkages

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1 Introduction

In recent decades, China has made extensive use of industrial policy with the stated aim of promoting technological upgrading and moving up the global value chain. A growing body of research finds that these policies have contributed to the expansion of targeted sectors and economic growth (Liu, 2019; Chen and Xie, 2019; Barwick et al., 2024), though others point to distortions, R&D crowding out, and reduced efficiency (Boeing, 2016; Howell, 2017; Barwick et al., 2024). While the domestic impacts of China's industrial policies are increasingly well documented, their international spillover effects remain far less understood. Such state-led interventions can affect other countries not only through direct competition by expanding export supply, altering global prices, or reshaping market competition, but also through production linkages embedded in global value chains. These linkages transmit through upstream and downstream channels, which can increase demand for imported intermediate goods or reduce reliance on foreign inputs through domestic substitution. This context raises a broader question: to what extent, and through which channels, does national industrial policy generate international spillovers?

To better understand these international spillovers, this paper empirically examines how China's high-tech industrial policies affected the German economy through upstream and downstream linkages. Germany provides an ideal setting: it is both a major exporter of high-tech products and a key trading partner of China. Specifically, I explain how German manufacturing industries responded to China's industrial policies targeting high-technology sectors. The analysis combines hand-collected data on China's product-level high-tech industrial policy targets with German administrative worker panel data, international trade flows, and input-output tables. Using a difference-in-differences (DiD) framework, I find that China's industrial policies increased German exports to China in upstream industries, suggesting that industrial upgrading in one country can create demand-side spillovers in its trading partners.

To estimate these effects, I exploit the staggered rollout of policy treatment across products and time within industries using a dynamic DiD framework with doubly robust estimators (Callaway and Sant'Anna, 2021). The design compares targeted and non-targeted products within each industry while allowing for industry-specific time trends, ensuring that results are not driven by structural differences across industries. I then aggregate product-level treatments to the industry level using crosswalk and an input-output matrix. This exposure design captures how industries are connected to policy-targeted products through input-output linkages, either by using targeted inputs or by supplying inputs to industries producing them. I measure two types of industry-level exposure: upstream exposure, for industries supplying inputs to industries producing treated products, and downstream exposure, for industries purchasing inputs from them. I compare outcomes across industries with varying exposure intensities, using 1998 as the pre-treatment baseline.

The analysis yields three main findings. First, China's industrial policies significantly boosted export performance and revealed comparative advantage in targeted high-tech products. Five years after treatment, treated products expand total exports by 42% more than never-treated products within the same industry. This effect is particularly pronounced for exports by joint ventures and wholly foreign-owned firms, as well as in processing trade, suggesting a potential role for foreign investment in amplifying the policies' impact. Revealed comparative advantage measured using the gravity model approach of Costinot et al. (2012) also improves: the export productivity of treated products relative to world average increases significantly after treatment. Both export and revealed comparative advantage effects rise gradually over time, indicating sustained long-term gains rather than one-time shocks.

Second, China's industrial policies significantly increased its bilateral trade with Germany, expanding exports in treated intermediate goods but also raising imports of treated capital equipment from Germany, reflecting limited domestic substitution capacity in these sophisticated products. China's exports to Germany grew mainly in processed industrial supplies and other non-capital goods, with no significant effect for treated final capital goods. By contrast, the import response was concentrated in final capital goods: five years after treatment, China imported about 57% more of treated final capital goods from Germany. Even with government support, substituting for foreign advanced capital equipment remains difficult. At the industry level, this asymmetry reflects the structure of production linkages. Chinese downstream industries that are more exposed to treated upstream inputs exported 28% more to Germany, while Chinese upstream industries imported 22% more from German suppliers. These results suggest that China's industrial policies not only strengthened its role as a key intermediate supplier in global value chains but also deepened its dependence on foreign advanced equipment, particularly from Germany.

Third, China's industrial policies generate significant spillovers in the German labour market, with different effects across upstream and downstream industries. German upstream industries facing stronger export demand from China expand full-time employment by 5% more than industries one standard deviation less exposed, accompanied by a 1.5% rise in average wages. On the other hand, German downstream industries that import more from China exhibit mild but statistically insignificant increases in full-time employment and average wages, possibly reflecting offsetting effects of cheaper imported inputs and substitution away from domestic producers. In addition, greater downstream exposure is associated with a 1-percentage-point increase (24% relative to sample average) in the share of engineers and a 2-percentage-point decline (3.3%) in the share of production workers. These results suggest that China's industrial policies contribute to expansion in Germany's upstream industries while shifting the occupational composition of downstream exposed industries toward higher-skilled workers.

To better understand the channels through which industrial policies affect trade and labour market outcomes, I explore the role of innovation as a potential mechanism. Chinese inventors filed, and were granted, significantly more patents in international patent classifications associated with treated products, suggesting that industrial policies foster not only scale effects in production and exports, but also technological upgrading. This innovation response is not limited to directly treated fields: downstream industries that purchase inputs from industries with treated products also show significantly greater patenting activity, consistent with the stronger export growth observed in these industries. In contrast, upstream industries do not exhibit any innovation response, suggesting that the technologies required in those industries remain largely sourced from abroad. This asymmetry is in line with the trade findings and supports the interpretation that China's industrial policies strengthen downstream competitiveness and rely on foreign technological inputs in upstream industries.

This paper contributes to the literature on industrial policy by providing new evidence on international spillovers transmitted through input-output linkages. A growing body of research has renewed interest in industrial policy, with advances in measurement (Juhász et al., 2025), theoretical modelling and welfare analysis (Bartelme et al., 2025), and empirical works emphasizing causal identification and policy heterogeneity (e.g., Juhász et al., 2024b). This paper highlights how China's high-tech industrialization policies affect foreign upstream suppliers and downstream buyers relying on subsidized inputs. It complements recent evidence on firm reallocation toward upstream and downstream activities in response to China's Five-Year Plans (Cen et al., 2024), as well as quantitative analysis (Liu, 2019) and sectoral studies (Lane, 2024; Huang et al., 2025; Alfaro et al., 2025) that demonstrate that industrial policies targeting upstream products can strengthen downstream competitiveness. Beyond trade effects, this paper also sheds light on the labour market consequences of industrial policy spillovers, including impacts on employment and occupational structure in foreign industries.

This paper also offers a new perspective on the "China Shock" literature by emphasizing the role of state-led industrial upgrading, beyond trade liberalization, in reshaping global production patterns. While a large body of work has documented the labour displacement effects of rising Chinese import competition (e.g., Autor et al., 2013; Pierce and Schott, 2016; Acemoglu et al., 2016), more recent studies highlight potential gains from access to cheaper Chinese intermediate inputs or reallocation of labour into related service sectors (Pierce et al., 2024; Bloom et al., 2024). This paper complements the literature by showing that China's export growth was not solely driven by trade liberalization but also by industrial policies that promote high-technology industries. Focusing on the Germany-China bilateral relationship, this paper builds on prior evidence of moderate adverse effects from rising Chinese imports on German industries (Dauth et al., 2014, 2021) and shows that China's industrial policies generated upstream demand shocks and downstream upgrading responses in Germany. These findings offer new insights on the "China Shock" literature by linking state-led industrial policy to global supply chain spillovers and documenting both challenges and adjustments at the technological frontier.

Finally, this paper contributes to the industrial policy literature by moving beyond industry-specific case studies to evaluate a broad, multi-sectoral policy with granular product-level targets. Existing research has provided rich evidence on how industrial policy targeted in individual sectors such as shipbuilding (Barwick et al., 2024), semiconductors (Bown and Wang, 2024; Juhász et al., 2024a), rare earths (Alfaro et al., 2025), and renewable energy (Xu et al., 2025), and heavy and chemical industries (Lane, 2024). This paper takes a complementary approach by analyzing a set of high-tech industrial policies with national scope and cross-sector coverage. This approach allows for more general insights into how industrial policy affect export performance of targeted industries, as well as upstream and downstream spillovers across industries.

The remainder of the paper is organized as follows: Section 2 provides institutional background on China's industrial policies aimed at promoting high-tech manufacturing; Section 3 describes the data sources used in the analysis; Section 4 presents product-level estimates of the direct effects of China's industrial policies on targeted products; Section 5 examines the international spillover effects through upstream and downstream linkages with a focus on German industries; Section 6 discusses potential mechanisms and extensions; and Section 7 concludes and discusses limitations.

2 Institutional Background

The Industrial Policy Targeted on High-tech Manufacturing. In the late 1990s, China's industrial structure was concentrated in resource-intensive and low-tech traditional sectors, despite rapid economic growth. Concerned about the long-term sustainability of such growth, the government sought to transform the economy by promoting advanced technologies, upgrading industrial capacity, and shifting toward more innovation-driven development.[1] As part of this effort, in 1999, the Chinese National Development and Reform Commission (NDRC) and the Ministry of Science and Technology (MOST) jointly issued the *Guidance on Current Priority Development of Key High-Tech Industrialization Sectors*. It was the first national policy guideline explicitly focused on high-tech industrial development, aiming to identify key areas for industrial upgrading and to direct resources toward advanced technologies with strong commercial and developmental potential.

The 1999 *Guidance* listed 138 priority areas across ten major sectors, including aerospace, information technology, biomedicine, new materials, advanced energy, advanced manufacturing, environmental protection, modern transportation, modern agriculture, and marine technologies. These areas were selected through expert consultation based on their alignment with national development needs, technological feasibility, and potential to drive industrial upgrading. Within each area, the *Guidance* listed specific products designated as current priorities for industrialization. The policy was subsequently revised in 2001, 2004, 2007, and 2011, with each update adding new areas, removing those deemed mature, and adjusting existing areas to reflect evolving policy priorities and technological progress.

In this paper, I define policy treatment at the product level based on the year a product was first listed in the *Guidance*. While the *Guidance* is a national policy guideline, it serves as a

[1] See *1999 Guidance on Current Priority Development of Key High-Tech Industrialization Sectors*.

central benchmark for implementing a range of industrial policy instruments. Figure 1 summarizes the major policy instruments associated with the *Guidance* and their implementing agencies. In collaboration with the Ministry of Finance (MOF) and the State Taxation Administration (STA), MOST is responsible for the certification of high-tech enterprises and associated tax incentives, such as pre-tax deductions for R&D spending. MOST also works with other departments, such as the Ministry of Commerce (MOC) and the General Administration of Customs, to implement export tax rebates and promote foreign investment in high-tech fields. Meanwhile, the NDRC manages government subsidies, including both central and local funding for high-tech industrialization, as well as specialized funding for selective projects and firms.

Local governments play a central role in implementing the *Guidance*. They typically operationalize the *Guidance* by circulating the national document, allocating local fiscal resources, and organizing applications for central fiscal programs or tax-related certifications. In some cases, local governments issue their own versions of the *Guidance*, adjusted to reflect comparative advantages and tailored to local industrial priorities. As shown in Figure 2, a large share of provincial governments adopted policy instruments that directly cited the *Guidance*, while others implemented related policies without explicitly referencing it. My empirical strategy identifies the effect of national policy framework by focusing on the year in which each product was first listed at the national level in the *Guidance*. While the implementation of these instruments is decentralized, the national listing year serves as a common trigger for their activation, which motivates using the product-year as the unit of analysis.

3 Data

3.1 Industrial Policy Data

I defined products treated by the industrial policies as those listed in the *Guidance*, which specifies products prioritized for industrialization. I manually compiled 1,136 product descriptions from all revisions of the *Guidance* and mapped them to 368 treated products at the 6-digit HS level (Details in Data Appendix A).[2]

The treatment year was defined as the first year each product appears in any revision of the

[2]Throughout the paper, I refer to these 368 products as *treated or targeted products*

Guidance. If multiple product descriptions mapped to the same HS code, I assigned the earliest year. While I also recorded the year in which an HS code was removed from the *Guidance*, the analysis focuses only on initial treatment, since policy effects may persist beyond formal removal. I exploited variation in treatment timing across products to estimate the effects of industrial policies. The identification strategy is detailed in Section 4.

Figure 3 summarizes the dynamics and composition of products treated by China's industrial policies across the five revisions of the *Guidance*. Panel (a) shows the number of treated products by United Nations Broad Economic Categories (BEC), which classify goods by broad economic function, end-use, and processing stage. Most treated products fell into two categories: capital goods (e.g., CNC machine tools and industrial robots) and processed industrial supplies (e.g., semiconductors and chemical products). This pattern suggests that the *Guidance* emphasized upgrading upstream production capacity rather than promoting final consumer goods (e.g., personal computers). Panel (b) plots the number of newly introduced, continuously listed, and removed products in each revision of *Guidance*. During the initial two waves, 228(62%) of all 368 treated products were first introduced, while 63 (17%) products were removed from the *Guidance* in subsequent revisions.

3.2 German Labour Market

To examine the international spillover effects of China's industrial policies on German labour markets, I constructed an industry-year panel using worker-level administrative data from the Sample of Integrated Labour Market Biographies (SIAB), provided by the German Federal Employment Agency. The SIAB data is a 2% random sample of the Integrated Employment Biographies, which includes all individuals employed in jobs subject to social security contributions. It contains complete employment histories for approximately 1.8 million individuals from 1975 to 2019. I restricted the sample to the period 1993–2017 due to the data limitations for East German workers and focused on full-time workers employed in manufacturing industries aged 18 to 55.

Each observation corresponds to an employment contract and includes start and end dates, employment status, 3-digit industry affiliation, occupation, workplace location, daily wage, and demographic information such as education, age, gender, and nationality. I aggregated the contract-level data to a worker-year panel by retaining each worker's main job within each year.[3] Because

[3]Main job is defined as the one with the longest tenure within a given year. If two jobs have equal duration, the

wages are top-coded for pension insurance purposes, I followed the imputation procedure proposed by Dauth and Eppelsheimer (2020) and deflated nominal wages using the Consumer Price Index.

3.3 Trade Data and Input-Output Linkages

I used international trade data from the CEPII-BACI database, which reports trade flows at 6-digit HS level starting in 1996. To capture heterogeneity, I supplemented it with Chinese Customs data (1997-2014), which disaggregates trade by firm ownership (domestic firms vs. foreign-invested firms) and trade type (ordinary vs. processing trade). I used a concordance table from the World Integrated Trade Solution (WITS) that maps 6-digit HS products to 4-digit ISIC (Rev.3) industries, which provided a harmonized framework compatible with both German labour market data and the Chinese input-output (IO) tables.

I used the 2007 Chinese IO Table from the National Bureau of Statistics to construct upstream and downstream linkages between industries. The 2007 IO Table is the earliest version that provides a detailed industry breakdown, comprising 135 industries.[4] After harmonizing the classification, I focused on a sample of 61 manufacturing industries, 32 of which include products directly targeted by China's industrial policies. Throughout the analysis, all references to "industry" refers to this harmonized set. Additional details on data sources and concordance mappings are provided in Data Appendix A.

3.4 Patent Data

Innovation outcomes are measured using patent data from the OECD Triadic Patent Families database, which tracks patents filed at all three major patent offices: the EPO, the Japan Patent Office (JPO), and the United States Patent and Trademark Office (USPTO). The triadic definition helps filter out lower-quality patents and provides a more reliable proxy for high-value innovation activity.

Patents are classified by 4-digit International Patent Classification (IPC) codes, and each patent-IPC combination is treated as a separate observation. I constructed a country-IPC-year panel based on applicants' country of residence and earliest filing year.

main job is defined as the one with the higher daily wage.

[4] For comparison, Germany's input-output table is much more aggregated, covering only 17 manufacturing industries.

To define treatment at the IPC level, I applied the crosswalk developed by Lybbert and Zolas (2014), which maps 6-digit HS codes to 4-digit IPC codes.[5] Among 639 IPC fields, 233 (36%) are classified as treated, most (73%) of which were first targeted in the initial two waves of the *Guidance* (1999, 2001). In the industry-level analysis, patent IPC codes are mapped to industries using weighted concordance tables. Further details are provided in Appendix A.

4 Direct Impacts of Industrial Policy

This section analyzes the effects of China's industrial policies on the export performance at the 6-digit product level. I first discuss the empirical strategy for estimating the dynamic effects of policy targeting, and then present the results for each outcome of interest.

4.1 Identification Strategy

I began by estimating the dynamic effect of the industrial policies on Chinese products' export performance. This identification strategy exploited the staggered rollout of treatment across granular products between 1999 and 2011, applying a staggered difference-in-differences (DiD) framework. My approach compared the before-after differences in outcomes between products eligible for government support and those that were never targeted.

Formally, I estimated the following equation:

$$y_{p,t} = \sum_{k} \beta_k \times \mathbf{1}\{t - G_p = k\} + \alpha_p + \alpha_{j(p),t} + \epsilon_{pt} \tag{1}$$

where the outcome variable $y_{p,t}$ includes total exports, revealed export productivity, as well as extensive margin and intensive margin on exports of product p in year t. Each product p was assigned a treatment year $G_p = \{1999, 2001, 2004, 2007, 2011, \infty\}$, where $G_p = \infty$ denotes the never-treated control group. The indicator $\mathbf{1}\{t - G_p = k\}$ equals one if year t is k years relative to the first treatment year of product p.

The specification includes product fixed effects as well as industry-by-year fixed effects to absorb industry-level shocks. This design therefore compares products within the same industry that differ

[5] I dropped mappings with a matching probability below 0.1 and manually excluded certain linkages based on a review of the IPC descriptions.

in their exposure to the industrial policies. In the absence of treatment, the export performance of products within an industry is assumed to evolved along parallel trends.

A standard two-way fixed effects (TWFE) model would assume homogeneous treatment effects across products and time, with the coefficient identifying the average treatment effect on the treated product (ATT). However, heterogeneity in product trajectories raised concerns about differential pre-trends. To address this, I estimated an event study specification to test for pre-treatment dynamics. As long as β_k is statistically insignificant in pre-treatment periods, the parallel trend assumption is credible. In addition, I implemented the estimator of Callaway and Sant'Anna (2021), which accounts for treatment heterogeneity and avoids forbidden comparisons with already treated units. This method decomposes the staggered DiD into a series of clean 2×2 comparisons between treated and never-treated units, estimates group-time-specific ATTs, and aggregates them across groups and time by group size.

4.2 Product-Level Results

Having established the empirical strategy, I now present the estimation results. I begin with first-stage estimates of how China's industrial policies affect overall export performance, followed by their impact on bilateral trade between China and Germany.

Export Expansion. Figure4(a) presents the baseline dynamic DiD estimates for the impact of China's industrial policies on total exports to the rest of world. Prior to treatment, exports of treated and never-treated products within the same industry evolved along similar trends. After treatment, however, exports of treated products grew more rapidly, with differences becoming statistically significant two years after initial treatment and widening over time. Five years after treatment, treated products exported about 0.4 log points more than never-treated products; by year ten, the difference reached 0.75 log points, equivalent to a 112% increase relative to baseline levels. Panel (c) and (d) decompose the aggregate effect into extensive and intensive margins. Following treatment, treated products were exported to a larger number of destinations, and—even within pre-existing destinations—export growth was significantly higher than for never-treated products. For the intensive margin, the effect appears immediately after treatment, as exports per existing destination rise at once. However, the magnitude of the effect is smaller than the aggregate export response in the long run, suggesting that much of the sustained growth is driven by the expansion into new export destinations.

Figures 4(e) and (f) further disaggregate exports by firm ownership and trade type. Both domestic firms, including private firms and state-owned enterprises, and foreign firms, including joint ventures and wholly foreign-owned enterprises, increased exports significantly after treatment. The point estimates were larger for foreign firms, although the differences relative to domestic firms were not statistically significant. This pattern is consistent with foreign firms' technological advantages and their ability to transfer productivity from overseas parent companies. A similar pattern holds across trade types. Industrial policies increased both ordinary and processing trade. Processing trade—where firms import duty-free inputs, process or assemble them and then re-export—showed larger point estimates, though not significantly different from estimates for ordinary trade using duty-paid or domestic inputs.

Revealed Comparative Advantage Improvement and Quality Upgrading. While the large export gains indicate strong policy effects on export volumes, it is important to examine whether these gains reflect improvements in China's comparative advantage in the treated products or simply scale effects driven by subsidies. I estimated a revealed comparative advantage index based on a structural gravity framework (CDK) following Costinot et al. (2012) and Leromain and Orefice (2014). A higher CDK index wou;d indicate that China is becoming relatively more productive in a given product compared to the world average. Details on the estimation procedure and index construction are provided in the Data Appendix A.

Panel (b) of Figure 4 presents the dynamic treatment effects on China's CDK index. Before treatment, treated products showed no differential trend relative to never-treated products, indicating that the *Guidance* did not target products already on a faster growth path. After treatment, the CDK index for treated products rises steadily relative to never-treated products within the same industry, reaching about 0.7 by year ten. This pattern suggests a gradual improvement of China's revealed comparative advantage in treated products.

One concern is that these improvements might simply reflect subsidized export expansion rather than quality upgrading. To examine this, I used two proxies for product quality: changes in unit export prices and the average GDP per capita of destination markets, weighted by export values.

Details of construction are provided in the Data Appendix A. The results, summarized in Columns (3) and (4) of Table 1, show that treated products experienced 7% higher growth in unit prices within five years after treatment and 10.6% higher growth during the subsequent five years. They were also increasingly exported to higher-income markets, with an average destination GDP per capita about USD 975 above that for never-treated products. Overall, these findings indicate that industrial policies not only expanded exports but also improved China's comparative advantage and promoted quality upgrading in the treated products.

China–Germany Bilateral Trade Flows. Having established that treated products experienced significant export growth globally, I examined the bilateral trade relationship between China and Germany. As both a major trading partner of China and a global leader in advanced manufacturing, Germany offers a compelling context to examine how industrial policies aimed at high-tech upgrading and technological catching-up in a developing country shape outcomes in a technological frontier economy. Figure 5 plots the effects of treatment on bilateral exports and imports. Consistent with the global pattern, Chinese exports of treated products to Germany increased significantly relative to never-treated products. At the same time, China's imports from Germany also rose following treatment, though the point estimates are smaller in magnitude than those for exports. The import response appeared counterintuitive given the industrial policies' objective of expanding domestic production, which motivated a closer look at what kinds of products drive the pattern.

To better understand these effects, I disaggregated the effects by product category using the Broad Economics Category classification and restricted comparisons within the same industry and BEC group.[6] The analysis focused on the three product groups: processed industrial supplies, final capital goods, and all other products (including consumer goods, transport equipment, and parts or components of capital goods, etc.).[7]

The right column of Figure 6 shows the estimated effects on China's imports from Germany by product group. The import response is concentrated in final capital goods: following treatment,

[6] I used the regression-based estimator from Callaway and Sant'Anna (2021), as a doubly robust estimator required large cell sizes, which may not be satisfied in all years or sample partitions.

[7] Processed industrial supplies refer to intermediate inputs used widely across manufacturing (e.g., chemicals, metal components), while parts or components of capital goods refer to capital-related intermediates (e.g., engines, machine parts) that are embedded in the production of final capital equipment.

China imported significantly more treated final capital goods from Germany relative to never-treated products. In contrast, there were no significant treatment effects for imports of processed industrial supplies or other products.

The left column of Figure 6 illustrates a different pattern for Chinese exports to Germany. Processed industrial supplies and other goods exhibited gradual post-treatment increases in the exports of treated products, with no evidence of differential pre-trends. The effects were persistent and precisely estimated, with point estimates rising steadily to about 1 log points by year ten. Exports of final capital goods, however, displayed smaller and less precisely estimated effects, becoming statistically significant only around five to seven years after the initial treatment.

Taken together, these heterogeneous bilateral trade patterns reflect the complementary positions of China and Germany in global production networks. The increase in China's exports to Germany was concentrated in processed industrial supplies and other products, suggesting that treated Chinese products increasingly served as upstream inputs for German manufacturing. Meanwhile, China's rising imports of final capital goods suggest continued reliance on advanced machinery and equipment from Germany to support China's domestic industrial upgrading. Notably, many of these capital goods are themselves targeted by Chinese industrial policies, suggesting that even with government support, advanced equipment remains difficult to substitute domestically when technological barriers are high.

China's Gain without Germany's Loss in Global Export Markets. Next, I examined whether China's industrial policies reshaped its broader position in global export markets. Specifically, I studied whether China's export expansion came at the expense of Germany.

To assess this, I constructed import market shares of Chinese and German products across destination countries. For each importer, I computed the share of imports of a given product from China in total imports of that product in year t, and used the import share as the outcome variable in equation 1. I constructed the same outcome for German products to allow a direct comparison of market-share dynamics. I grouped importer countries by income levels, following the World Bank classification into high-income, upper-middle, lower-middle, and low-income groups. I excluded both China and Germany from the sample of importers.

Figure 7 shows the estimated average treatment effects on the import shares of Chinese and

German products during the first and second five-year periods after treatment. China's share of global imports increased modestly in low-income markets within the first five years, but became significantly larger in both high- and low-income markets over the subsequent period. Specifically, the share of Chinese products increased by 2 percentage points in low-income markets (a 30.5% increase relative to the baseline average) and by 1.2 percentage points in high-income markets (a 30% increase). However, Germany's market share in the same markets remained stable, indicating no evidence of displacement. In other words, China's export growth happened without Germany's loss of global market share.

4.3 Robustness to Potential Confounding Policies

A potential concern for identification is that other national policies, such as the tenth and eleventh Five-Year Plans (FYPs, 2001–2010), may confound the effects attributed to the high-tech industrial policies. While FYPs specify industry priorities to guide overall economic development, they seldom identify specific policy instruments and product-level interventions like the *Guidance*. However, industries highlighted in the FYPs may have received complementary support, potentially biasing the comparison downward if some control-group industries benefited from such support.

A more specific threat arises from capacity control policies implemented in heavy industries (e.g., steel, aluminum, cement) in the early 2000s. Unrelated to the *Guidance*, these policies affected exports through production restrictions and export promotions. If such industries were included as untreated controls, they may distort the estimated treatment effects.

Another concern is that some products in the never-treated group may nonetheless have received support from other product-level policies related to high-tech promotion but not explicitly targeted by the *Guidance*. As shown in Figure 1, I considered two such confounders: (1) products listed in the official Catalogue of High-Tech Products, which qualified for tax incentives such as R&D pre-tax deductions and reduced corporate income tax rates; and (2) products included in the Catalogue of Encouraged High-Tech Exports, which benefited from preferential export tax rebates. While *Guidance*-targeted products are also eligible for these instruments, both catalogues are broader in scope and include high-tech goods not designated as industrialization priorities. Including these products in the control group would likely have biased the estimates downward.

To mitigate these sources of potential confounding policies, I implemented several adjustments.

First, I included industry-specific time trends in the main specification to absorb any time-varying shocks or policy interventions at the industry level, addressing concerns related to the FYPs. Second, I conducted robustness checks excluding products directly affected by capacity control policies as well as those eligible for the high-tech tax or export incentives described above.

The robustness results, presented in Appendix Figure 14, confirm that the main findings are robust. Excluding products affected by capacity control policies produced estimates very close to the baseline results, as most of these products belong to industries without any *Guidance*-targeted products and were therefore dropped from the sample. By contrast, estimates excluding products covered by the high-tech catalogues were slightly larger in magnitude, consistent with expectations of downward bias when such products remain in the control group. These adjustments strengthen the credibility of the identification strategy by better isolating variation tied to the national high-tech industrial policies. Nevertheless, given the complexity of China's policy environment (Fang et al., 2025), these robustness checks cannot fully eliminate all sources of confounding. Therefore, the main estimates should be interpreted as conservative lower-bound effects of high-tech industrial policies exposure.

5 Upstream and Downstream Impacts on German Industries

Beyond product-level impacts, China's industrial policies may generate broader international spillovers through production networks. This section examines the industry-level analysis based on the upstream and downstream exposure to the industrial policies. I first describe the measurement for upstream and downstream exposure and the identification strategy. Then, I present estimates of the average impact of industrial policies on industries with upstream and downstream exposure.

5.1 Identification Strategy

To evaluate international spillovers, I examined how industrial policies affect industries through input–output linkages. Specifically, I constructed measures of upstream and downstream exposure that capture an industry's connection to the treated industries whose products are directly targeted by the policy. An industry experiences upstream exposure if it supplies inputs to treated industries and is thus affected through demand spillovers. Conversely, it experiences downstream exposure if it purchases inputs from the treated industries and is affected via supply-side changes. Following the method in Lane (2024), I measured an industry's exposure to the high-tech industrial policies using China's 2007 input–output table. Specifically, industry i's upstream and downstream exposures were defined as:

$$\text{Upstream Exposure}_i = \sum_j \frac{x_{ij}}{y_j} \times \frac{\sum_{p \in \mathcal{P}_j^{\text{treated}}} \text{export}_{p,t_o}}{\sum_{p \in \mathcal{P}_j} \text{export}_{p,t_0}} \tag{2}$$

$$\text{Downstream Exposure}_i = \sum_j \frac{x_{ji}}{y_i} \times \frac{\sum_{p \in \mathcal{P}_j^{\text{treated}}} \text{export}_{p,t_o}}{\sum_{p \in \mathcal{P}_j} \text{export}_{p,t_0}} \tag{3}$$

where j indexes manufacturing industries, x_{ij} denotes the value of industry i's output sold to industry j, and y_j is the total output of industry j. Upstream exposure of i equals the weighted average treatment intensity across all industries, where treatment intensity is the export share of products targeted by the industrial policies within industry j, and the weight $\frac{x_{ij}}{y_j}$ denotes the value of i's output sold to j as a share of j's total value of output in the input–output matrix. The export share is measured by the export value of targeted products over all products within the industry for baseline years 1996–1998, excluding export values from China to Germany. Industries with large upstream exposure are the key suppliers to industries with high concentrations of targeted products. Similarly, downstream exposure equals the weighted average of the treatment intensity across all industries, where the weight $\frac{x_{ji}}{y_i}$ represents the share of industry i's inputs purchased from industry j. These two measures capture first-order spillovers based on an industry's role as a supplier or buyer relative to treated industries. While the main analysis focused on first-order linkages, I additionally tested the robustness using full linkages derived from the Leontief inverse matrix, which captures both direct and indirect propagation of industrial policies across the entire input–output linkages (See Appendix Figure 15).

When aggregating product-level treatments to the industry level, industries differ in both the timing and the intensity of exposure for three reasons. Firstly, within a given industry, products can be targeted in different policy waves and represent varying shares of total exports. Secondly, if each industry is assigned its earliest treatment year, most are treated in the first two waves (1999 or 2001). Thirdly, when combining treatment with input–output linkages, industries become interconnected: a later-treated industry (e.g., 2001) may be indirectly affected earlier through its upstream or downstream linkages to industries treated in 1999. Given this overlap and interdependence across industries, it is empirically difficult to define separated treatment cohorts. I therefore treated 1999 as the common treatment year for all industries.

To estimate the impact of China's industrial policies through these linkages, I compared outcomes across industries with continuous exposure intensities:

$$\begin{aligned} y_{jt} = &\sum_{k\neq 1998} \beta^k (\text{Upstream}_j \times \text{Year}_t^k) + \sum_{k\neq 1998} \gamma^k (\text{Downstream}_j \times \text{Year}_t^k) \\ &+ \sum_{k\neq 1998} (\Omega_j \times \text{Year}_t^k) + \alpha_j + \alpha_t + \epsilon_{jt} \end{aligned} \tag{4}$$

where the outcome variable y_{jt} includes industry-level China–Germany bilateral trade flows, total full-time employment, and average daily wage of full-time workers, residualized on federal state, gender, nationality, and age. I estimated the specification with a TWFE model, with all coefficients interpreted relative to the 1998 baseline year. For labour market outcomes, I additionally controlled for baseline industrial characteristics Ω_j, including the share of university-educated workers, the share of female workers, the share of foreign-affiliated workers during 1995-1998, and changes in the industry's share of total employment over 1987–1992. All pre-treatment industry characteristics are interacted with year dummies to allow their effects to vary flexibly over time. The coefficients of β^k and γ^k capture the differential evolution of industries with one standard deviation higher upstream or downstream exposure. This specification allowed for differential post-treatment trajectories by exposure type, while controlling for industry and year fixed effects. The regressions are weighted 1998 employment, the year before treatment, and standard errors are clustered at the industry level.

5.2 Results

In this section, I first report estimates for bilateral trade outcomes between China and Germany, followed by labour market responses in Germany.

Asymmetric Upstream and Downstream Bilateral Trade. Panel (a) of Figure 8 shows that industries with higher downstream exposure experienced a significant and persistent increase in exports to Germany following the policy implementation. The effect becomes economically meaningful within five to eight years, peaking at approximately 0.3–0.4 log points, equivalent to a

35%–50% increase relative to less-exposed industries. In contrast, panel (b) shows that downstream exposure had no consistent impact on imports from Germany, with point estimates fluctuating around zero and confidence intervals remaining wide and overlapping.

Panel (c) and (d) displays the dynamic effects of upstream exposure. There was no significant effect on exports to Germany: point estimates trended upward only modestly after year seven and remained statistically insignificant from zero. However, imports from Germany responded strongly to upstream exposure: industries with greater upstream exposure exhibited a gradual and statistically significant increase in imports, reaching around 0.2 log points (roughly 22% growth) in the medium run, with effects persisting over time.

These asymmetric patterns are consistent with vertical specialization and position in global supply chain. Industries with greater downstream exposure expanded their exports to Germany without increasing their dependence on German inputs, suggesting that China's industrial policies effectively improved domestic production capacities in upstream industries, thereby enhancing the export of downstream users. In contrast, industries with greater upstream exposure increased their imports from Germany, reflecting rising demand for foreign upstream goods that, as targeted industries expand, were needed to scale or upgrade production. This asymmetric trade response highlights how China's industrial policies reshape bilateral trade flows through upstream and downstream linkages. Downstream industries expanded exports and benefited from improved domestic inputs. Upstream industries relied increasingly on foreign technological imports to meet rising demand.

German Labour Market Effects. Beyond the documented trade responses, China's industrial policies may have real economic consequences in partner countries. I examined whether these shifts in trade flows translated into labour market impacts by analyzing full-time employment, average daily wage, and occupational composition across German industries with varying exposure to China's industrial policies. I estimated the same specification as in Equation (4).

Figure 9 reports the effects of a one-standard-deviation increase in exposure on full-time employment and average daily wage, and Figure 10 presents results for within-industry share of engineers and production workers (the latter of which includes technicians and manual labour). Panels (a) and (b) of Figure 9 show that industries with greater downstream exposure experienced mild employment and wage gains. Although the point estimates are positive, the confidence intervals are wide and the effects are imprecisely estimated. The findings may reflect offsetting forces: downstream-exposed industries benefited from access to cheaper Chinese products, which reduced production costs and eased price pressures, thereby contributing to more employment and higher wages. At the same time, the increased direct imports from China may have substituted for domestic production. Consistent with this interpretation, Figure 10 panels (a) and (b) show clear evidence of occupational upgrading: industries with one standard deviation higher downstream exposure experienced a 1-percentage-point increase (24% relative to sample average) in the share of engineers and a 2-percentage-point decline (3.3%) in the share of production workers.

In contrast, German industries with greater upstream exposure experienced a significant and sustained increase in full-time employment, reaching approximately 5% relative to less-exposed industries over time. While there are signs of a mild upward drift in wages during 1993–1994 relative to the 1998 baseline, the pre-trend is not significant in the more recent pre-treatment years (1995–1998). After treatment, the wage effects strengthened gradually, becoming statistically significant after about five years and reaching roughly 1.5% above less-exposed industries by year seven. Unlike downstream exposure, upstream exposure was not associated with notable shifts in occupational composition: the shares of engineers and production workers both remained broadly stable over time. Appendix Figure 16 further shows that the expansion in full-time employment occurred primarily through increased hiring of production workers and new entrants under age 30. These findings suggest that upstream industries initially accommodated rising demand from China by hiring additional production and young workers at existing wage levels before aggregate wage pressures gradually emerged.

These results are consistent with the vertically specialized response to China's industrial policies. German upstream industries, which supply inputs to Chinese industries with treated products, benefited from increased demand due to the industrial policies, reflected in rising employment and wages without significant occupational reallocation. Conversely, downstream industries facing stronger import competition from China did not experience significant job displacement, with point estimates indicating modest gains in employment and wages, although these effects are not precisely estimated. At the same time, these industries exhibited clear patterns of within-industry reallocation: the relative share of engineers increased, while manual and production tasks declined.

This pattern reflects a form of task reallocation: German downstream industries specialized further into higher-skill jobs in response to growing availability of Chinese products supported by industrial policies. Overall, these findings demonstrate that China's industrial policies not only reshape trade patterns but also generate significant labour market responses in advanced economies like Germany.

6 Mechanisms

6.1 Innovation

The previous sections demonstrate significant effects of China's industrial policies on trade patterns and the German labour markets. Beyond the trade-related spillovers, industrial policies may also operate through technological upgrading and innovation. To explore this mechanism, I examined the policies' impact on patenting activity as a proxy for innovation.

To quantify the effects on innovation, I estimated the specification in Equation (1), where p indexes 4-digit IPC codes and j denotes the broader technological category. I focused on patent counts separately for Chinese and German inventors, asking whether China's industrial policies stimulated domestic innovation and whether they generate international spillovers in innovation. Given the large number of zero observations in China's patent counts in the early 1990s, a log transformation needed to be adjusted. As Chen and Roth (2024) point out, commonly used transformations such as $log(1 + Y)$ and $arcsinh(Y)$ yield average treatment effects that are difficult to interpret as percentage changes. I followed one of their recommended transformations: $m(y)$, $m(y) = log(y)$ for $y > 0$ and $m(0) = -1$. This approach ensured that the extensive-margin effect of transitioning from zero to one patent was treated equivalently to a one log-point increase on the intensive margin.[8]

Figure 11 presents the estimated effects at the IPC level. Panel (a) showed no evidence of differential pre-trends between treated and never-treated IPC codes within the same technological category. Following the policy treatment, however, Chinese inventors filed and were granted significantly more patents in treated IPCs relative to never-treated IPCs. Five years after treatment, patenting activity was approximately 25% higher in treated IPCs, with the divergence continuing to grow in subsequent years. By contrast, Panel (b) showed muted responses among German in-

[8]For example, $log(y_1) - log(y_0) = 1$.

ventors. While there was a statistically significant increase in patent activity around four years post-treatment, the magnitude was small and the growth remained relatively flat over time.

While the IPC-level analysis reveals that China's industrial policies stimulated patenting activity in targeted technological areas, it does not capture how these innovations propagate into broader industry-level dynamics through the production networks. To address this limitation, I turned to industry-level data and examined innovation outcomes respond to upstream and downstream exposure. Specifically, I estimated the specification in Equation (4), using the total number of granted patents within each industry as the dependent variable. This industry-level perspective allowed me to assess how innovation responses differ across industries more or less exposed to the industrial policies, either as upstream suppliers or downstream users of treated inputs.

Figure 12 presents estimated effects on industry-level patenting activity in China, in panels (a) and (b), and in Germany in Panels (c) and (d). There was no evidence of significant patent growth in Chinese industries with greater upstream exposure, suggesting that the industrial policies do not strongly incentivize innovation among upstream suppliers. In contrast, Chinese industries with greater downstream exposure exhibited a significant increase in patenting activity following treatment. This pattern implies that China's industrial policies generated innovation incentives among downstream industries, potentially by improving access to higher quality or lower-cost upstream inputs targeted by the policy, which in turn facilitated greater R&D investment.

By contrast, panels (c) and (d) show that China's industrial policies did not generate corresponding innovation spillovers in Germany. Neither upstream nor downstream German industries exhibited a significant change in patenting activity following the treatment, suggesting that the innovation effects were mainly domestic, with limited international spillovers through the innovation channel, which is different from the spillovers observed in the trade and employment outcomes.

6.2 Capability and Complexity

While innovation plays a critical role in realizing the long-term gains from industrial policies, the patterns of innovation response are heterogeneous across sectors. Since innovation tends to be more intensive in technologically complex products, this heterogeneity raises the question of whether policy effects are stronger for products with higher complexity, which typically require greater technological capabilities, higher fixed costs, and longer development cycles. Such products are also more likely to face financing and coordination constraints that government interventions can help alleviate. To explore this heterogeneity, I estimated the treatment effects across products of varying complexity.

I used product-level complexity measurements from Hausmann et al. (2014), which infer technological complexity at both country and product level based on global export patterns. A *country* is defined as more complex if it exports more products that few other countries export. A *product* is defined as more complex if it is mainly exported by more complex exporting countries. In 1998, China ranked 41st among 141 exporters in terms of complexity, while Germany ranked second, following Japan. These measurements provide a way to distinguish between relatively simple and complex products within industries, enabling an analysis of whether industrial policies have differential effects across the product complexity.

To implement this heterogeneity analysis, I first took the average complexity for each 4-digit HS product between 2000 and 2010. Then, I classified products as high-complexity if their complexity measure was above their industry median; otherwise, they were classified as low-complexity products. Finally, I aggregated the product-level trade flows into industry level by complexity group, and estimated equation 4 separately for low- and high-complexity trade.

Figure 13 plots the industry-level effects of China's industrial policies on bilateral trade between China and Germany, distinguished by product complexity. While the differences across low- and high-complexity products were not statistically significant, the patterns offer suggestive insights into potential mechanisms. In particular, panel (a) shows that the export growth of Chinese industries with greater downstream exposure was qualitatively larger for high-complexity products than for low-complexity ones. This finding is consistent with the innovation evidence in section 6.1, where downstream industries showed stronger patenting responses. Together, the stronger innovation responses and export growth in complex products suggest that industrial policies may have indirectly stimulated technological upgrading in downstream industries, enabling them to export more complex products.

Conversely, panel (d) indicates that China's import growth from German upstream industries was also more pronounced for high-complexity products than for low-complexity ones. While the estimates are again not statistically distinguishable across groups, the qualitative difference supports the interpretation that Chinese firms continued to rely on advanced foreign inputs.

These results point to two potential channels through which industrial policies operate: by stimulating innovation and upgrading in downstream industries, and by reinforcing reliance on foreign high-tech inputs in upstream industries.

6.3 Implications Beyond Germany

While this paper focuses the case of Germany, these spillovers effects are not unique to the German context. I conducted a similar analysis for China's trade flows with the rest of world, disaggregated by product complexity (low vs. high), and by trading partner capability (countries ranked below or above China in the export capability index of Hausmann et al. (2014)). As shown in Appendix Figures 17 and 18, the patterns of downstream export growth and upstream import growth also held at the global level. Chinese downstream industries expanded exports to both low- and high-capability countries, while the increase in upstream imports was qualitatively larger for high-capability countries. These findings suggest that other high-capability countries—especially those with comparative advantage in high-tech machinery and industrial equipment, such as Japan—may experience similar labour market effects as Germany, particularly in upstream industries that supply advanced inputs to Chinese production.

In addition to these patterns, Chinese upstream industries exposed to industrial policies also expanded exports to low-capability countries. A possible explanation is that the industrial policies stimulated domestic upstream production as demand expanded. Yet, these domestically produced inputs appear insufficiently technology-intensive to substitute advanced foreign goods and are thus not exported to high-capability markets.

7 Conclusion

This paper shows that China's industrial policies targeting high-technology manufacturing have significantly promoted the development of targeted products, both in terms of export performance and innovation. The policies also foster export expansion and technological upgrading in downstream industries that use these targeted upstream inputs.

These developments generate international spillovers to Germany, one of China's largest trading partners and a global leader in high-technology exporting. On the one hand, as Chinese firms scale up high-tech production, their demand for upstream equipment and inputs also rises. In the absence of sufficient domestic innovation in upstream industries, Chinese firms continue to rely on imports of advanced foreign inputs, particularly capital equipment. As a result, German upstream industries exposed to China's policy-induced demand expand their exports to China, along with employment growth and rising average daily wage. On the other hand, German downstream industries become exposed by importing increasing greater numbers of Chinese products that use targeted upstream inputs. This leads to shifts in employment composition toward higher-skilled occupations, without significant aggregate employment losses. Despite these trade and labour market adjustments, there is little evidence of innovation responses among German firms. The observed spillover effects appear largely driven by scale expansion, rather than induced technological upgrading.

While this paper sheds light on the international spillover effects of China's industrial policies, several limitations remain. First, my analysis focuses on a series of policies implemented between 1999 and the early 2000s, a period when China was still far from the global technological frontier. As such, the findings may not generalize to more recent industries policies, such as *Made in China 2025* or recent industry-specific policies targeting semiconductors and electric vehicles, especially given China's position in the global economy. The nature of international spillovers may evolve over time: during the catch-up phase, China may have complemented advanced economies like Germany; but as China approaches the frontier in certain sectors, competition pressures could emerge, potentially reshaping global market dynamics. Moreover, the analysis captures the broad effects of industrial policies on high-tech manufacturing, making it difficult to assess costs or identify which targeted interventions were most effective. Future research could explore these questions through more granular, sector-specific studies and by examining the dynamic effects of industrial policies in later stages of development.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*.

Alfaro, L., Harald Fadinger, Jan S. Schymik, and Gede Virananda (2025). Trade and Industrial Policy in Supply Chains: Directed Technological Change in Rare Earths. *NBER Working Paper*.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168.

Bartelme, D., Costinot, A., Donaldson, D., and Rodriguez-Clare, A. (2025). The Textbook Case for Industrial Policy: Theory Meets Data. *Journal of Political Economy*.

Barwick, P. J., Kalouptsidi, M., and Zahur, N. B. (2024). Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry. *The Review of Economic Studies: forthcoming*.

Bloom, N., Handley, K., Kurmann, A., and Luck, P. A. (2024). The China Shock Revisited: Job Reallocation and Industry Switching in U.S. Labor Markets. *NBER Working Paper*.

Boeing, P. (2016). The allocation and effectiveness of China's R&D subsidies - Evidence from listed firms. *Research Policy*, 45(9):1774–1789.

Bown, C. P. and Wang, D. (2024). Semiconductors and Modern Industrial Policy. *Journal of Economic Perspectives*, 38(4):81–110.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Cen, X., Fos, V., and Jiang, W. (2024). How Do U.S. Firms Withstand Foreign Industrial Policies? *NBER Working Paper*.

Chen, J. and Roth, J. (2024). Logs with Zeros? Some Problems and Solutions. *The Quarterly Journal of Economics*, 139(2):891–936.

Chen, J. and Xie, L. (2019). Industrial policy, structural transformation and economic growth: Evidence from China. *Frontiers of Business Research in China*, 13(1):18.

Costinot, A., Donaldson, D., and Komunjer, I. (2012). What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas. *The Review of Economic Studies*, 79(2):581–608.

Dauth, W. and Eppelsheimer, J. (2020). Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis: A guide. *Journal for Labour Market Research*, 54(1):10.

Dauth, W., Findeisen, S., and Suedekum, J. (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association*, 12(6):1643–1675.

Dauth, W., Findeisen, S., and Suedekum, J. (2021). Adjusting to Globalization in Germany. *Journal of Labor Economics*, page 55.

Fang, H., Li, M., and Lu, G. (2025). Decoding China's Industrial Policies. *SSRN Electronic Journal*.

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., and Yildirim, M. A. (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. The MIT Press. The MIT Press, Cambridge.

Howell, A. (2017). Picking 'winners' in China: Do subsidies matter for indigenous innovation and firm productivity? *China Economic Review*, 44:154–165.

Huang, Y., Baquie, S., Jaumotte, F., Kim, J., Lu, Y., Rafael Machado Parente, and Samuel Pienknagura (2025). Do Industrial Policies Increase Trade Competitiveness? *IMF Working Papers*.

Juhász, R., Goldberg, P. K., Nathan J. Lane, Giulia Lo Forte, and Jeff Thurk (2024a). Industrial Policy in the Global Semiconductor Sector. *NBER Working Paper*.

Juhász, R., Lane, N., and Rodrik, D. (2024b). The New Economics of Industrial Policy. *Annual Review of Economics*.

Juhász, R., Lane, N. J., Oehlsen, E., and Perez, V. C. (2025). Measuring Industrial Policy: A Text-Based Approach. *NBER Working Paper*.

Lane, N. (2024). Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea. *Quarterly Journal of Economics, Accepted*.

Leromain, E. and Orefice, G. (2014). New revealed comparative advantage index: Dataset and empirical distribution. *International Economics*, 139:48–70.

Liu, E. (2019). Industrial Policies in Production Networks. *The Quarterly Journal of Economics*, 134(4):1883–1948.

Lybbert, T. J. and Zolas, N. J. (2014). Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, 43(3):530–542.

Müller, K., Xu, C., Lehbib, M., and Chen, Z. (2025). The Global Macro Database: A New International Macroeconomic Dataset.

Pierce, J. R. and Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review*, 106(7):1632–1662.

Pierce, J. R., Schott, P. K., and Tello-Trillo, C. (2024). To Find Relative Earnings Gains After the China Shock, Look Outside Manufacturing and Upstream. *NBER Working Paper*.

Xu, D. Y., Gerarden, T. D., and Reguant, M. (2025). The Role of Industrial Policy in the Renewable Energy Sector. *NBER Working Paper*.

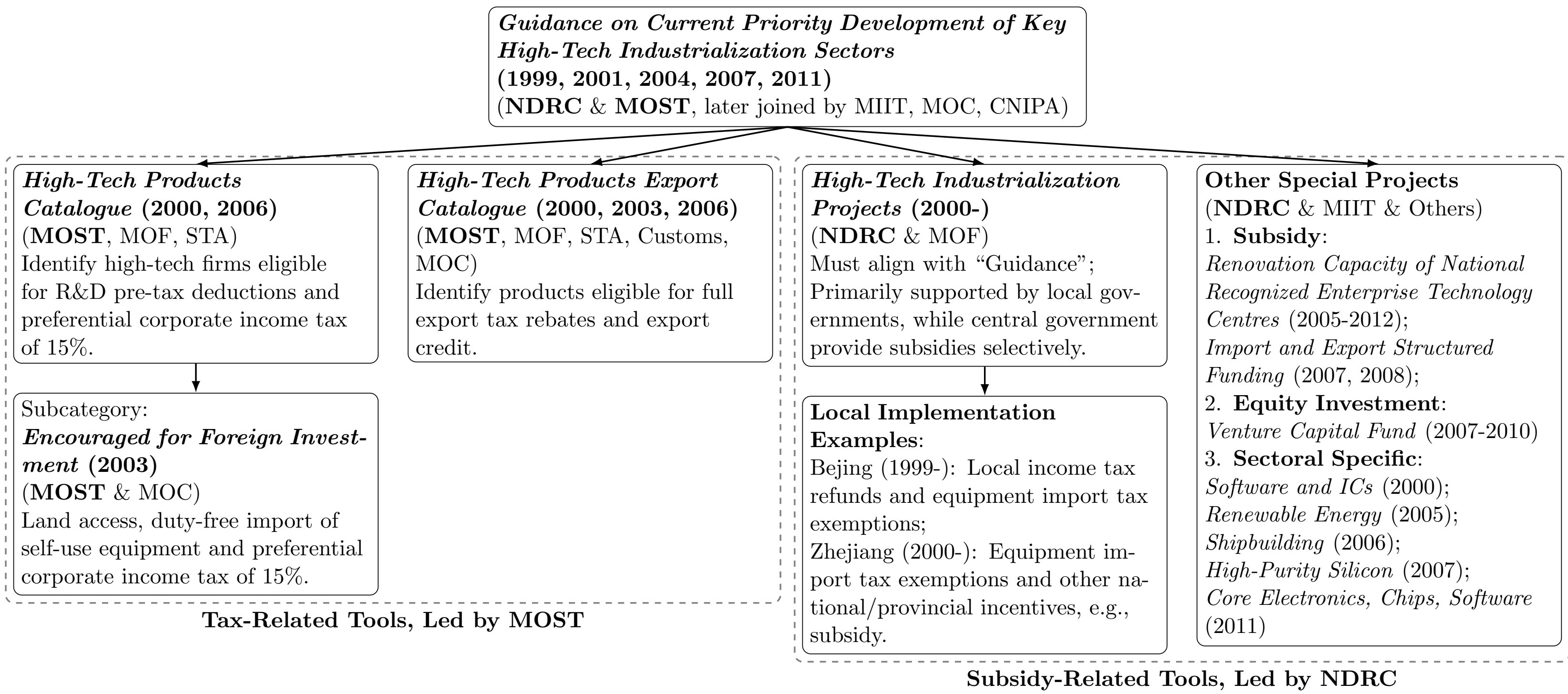
Tables

Table 1: Average Treatment Effects on Export Competitiveness and Export Quality

	Competitiveness		Quality Upgrading	
	(1)	(2)	(3)	(4)
	RCA(CDK)	RCA(Balassa)	Unit Price(log)	Destinations' GDPpc
Post (0 to 4)	0.016***	0.058**	0.070*	95.018
	(0.00)	(0.03)	(0.04)	(329.88)
Post (5 to 9)	0.051***	0.184***	0.106**	975.486**
	(0.01)	(0.06)	(0.05)	(427.54)
Pre (-5 to -1)	-0.001	-0.009	0.001	-73.806
	(0.00)	(0.01)	(0.02)	(122.51)
Ind×Year FE	Y	Y	Y	Y
Observations	67,807	69,531	68,908	69,135

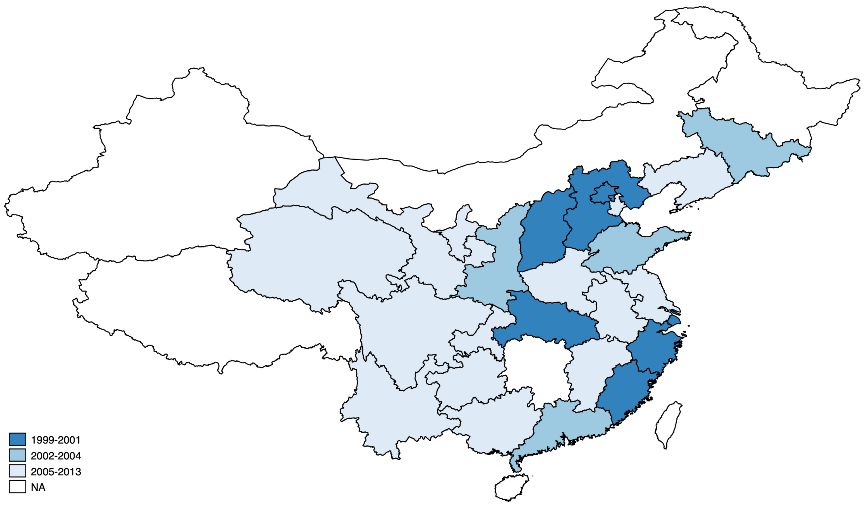
Notes: This table reports estimated average treatment effects on the treated (ATTs) across alternative outcome measures. Treatment is defined as the first year in which each 6-digit product was included in the *Guidance*. ATTs are estimated for three periods relative to treatment: 1–5 years before, 1–5 years after, and 6–10 years after treatment. Outcomes variables are specified by column: (1) Revealed comparative advantage (RCA) based on gravity-equation measures following Costinot et al. (2012); (2) RCA measured by the classic Balassa index; (3) export unit price (log); (4) export-weighted average GDP per capita across all export destinations. The number of observations refers to all product-year observations used to estimate the ATTs over the 1996–2017 period. Robust standard errors clustered at the product level are reported in parentheses.

Figures

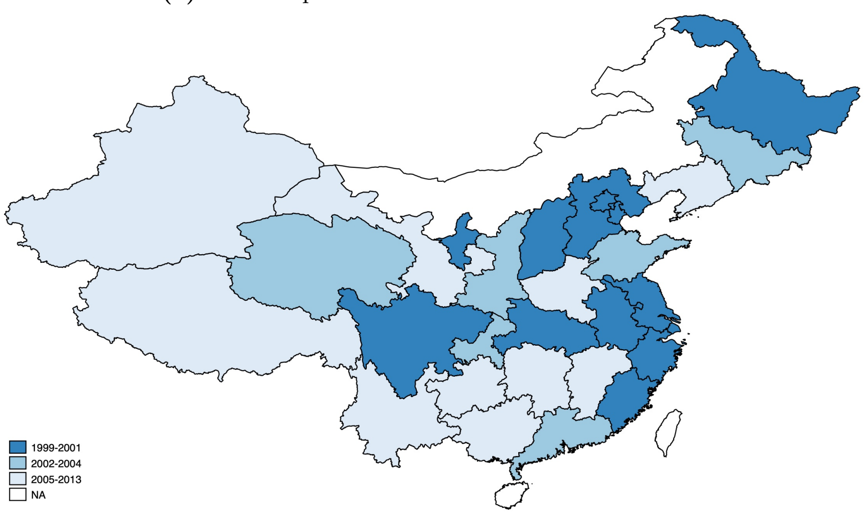


Note 1: NDRC: National Development and Reform Commission; MOST: Ministry of Science and Technology; MOF: Ministry of Finance; STA: State Taxation Administration; MOC: Ministry of Commerce; Customs: General Administration of Customs; MIIT: Ministry of Industry and Information Technology; CNIPA: China National Intellectual Property Administration.
Note 2: 2008 update of eligible high-tech firms for R&D pre-tax deductions: firms working on "Guidance" projects.
Note 3: Export tax rebates are typically funded by the provincial tax bureau, with each province may set its own criteria such as based on local "Guidance".

Figure 1: Institutional Framework of China's High-Tech Industrialization Policies



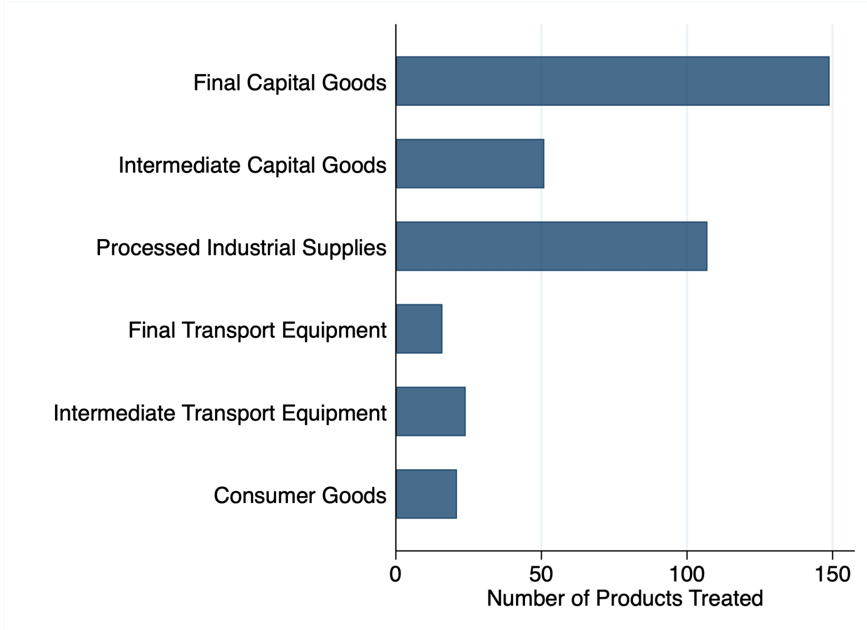
(a) Local Implementation: Direct Cited *Guidance*



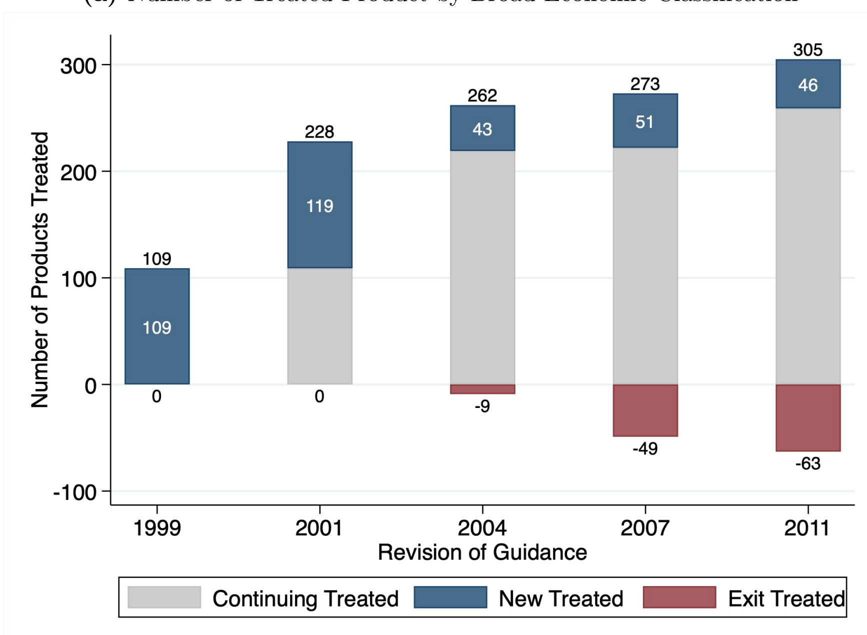
(b) Local Implementation: All Related

Figure 2: Earliest Local Implementation of *Guidance*

This figure shows the earliest year when each provincial government implemented any local policy tool: **(a)** policies that directly cite the *Guidance*; **(b)** all related policies, as long as the type of subsidy project aligns with national-level policy that are required to be consistent with the *Guidance*.
Tax-related tools include policies such as pre-tax deduction of R&D expenses, reduction of corporate income tax rate to 15%, export tax rebates, and tariff exemptions for imported equipment. Subsidies refer to direct funding support from central or local governments as well as interest rate subsidies on industrial loans.



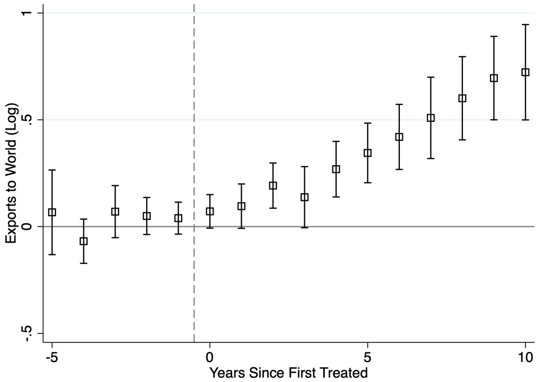
(a) Number of Treated Product by Broad Economic Classification



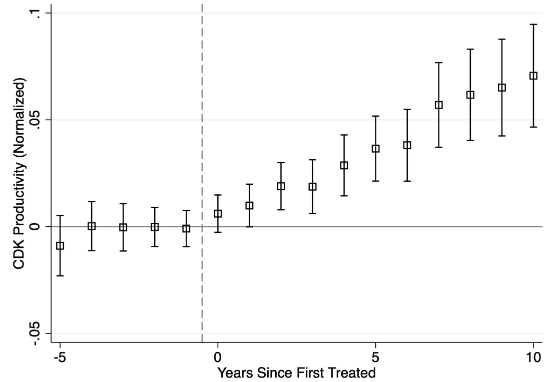
(b) Treated Product Dynamics by Revision of *Guidance*

Figure 3: Summary of Treated Products

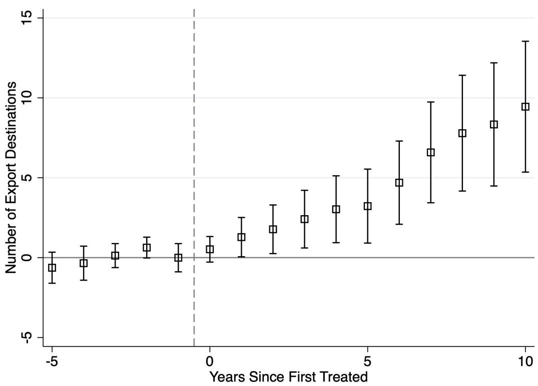
This figure summarizes the dynamics and composition of products targeted by China's industrial policies over five major revisions of the *Guidance*.
Panel (a) shows the distribution of treated products by Broad Economic Categories (BEC), following the United Nations Broad Economic Categories (BEC) system. **Panel (b)** shows the number of products newly treated, continuously treated, and exited (cumulative) from the treatment status following each revision of the *Guidance*. A product is considered "treated" if it is explicitly listed in the official document in the given revision year.



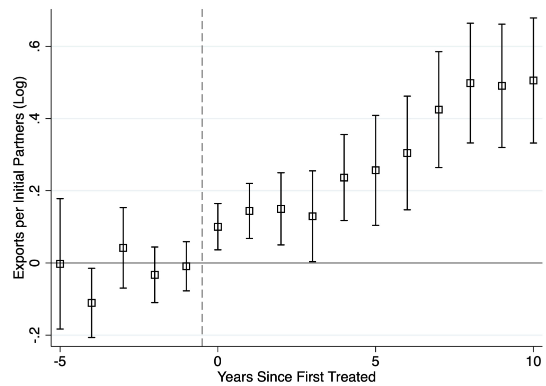
(a) Exports to World (Log)



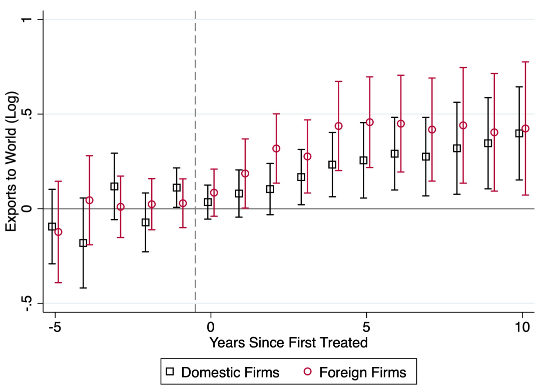
(b) CDK Productivity



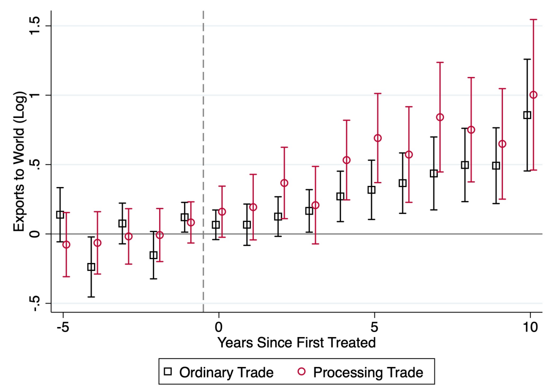
(c) Extensive: Number of Export Destinations



(d) Intensive: Exports per Initial Destination



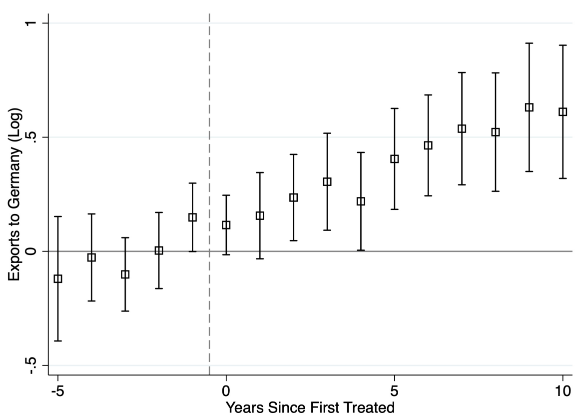
(e) Exports to World (Log) by Firm Ownership



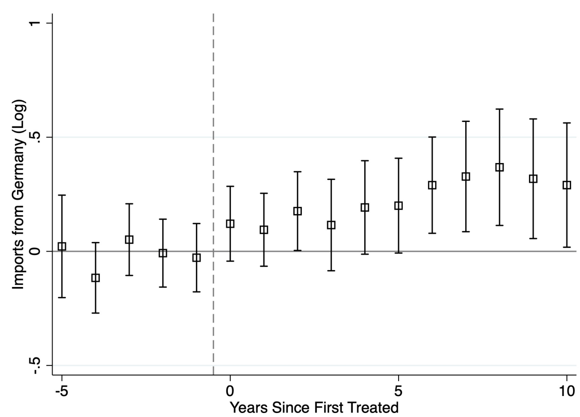
(f) Exports to World (Log) by Trade Type

Figure 4: Product-level Effect on Exports, Productivity, and Innovation

This figure plots the average treatment effects relative to the first year in which each product was introduced in the *Guidance*. The control group consists of never-treated products within the same industry. Robust standard errors are clustered at 6-digit product level, and the 95% CIs are reported. **Panel (a):** China's total exports to world (log). **Panel (b):** Estimated revealed export productivity following Costinot et al. (2012), normalized by corresponding U.S. product productivity. **Panel (c):** Number of China's total export destinations per product. **Panel (d):** China's average exports per export destination (log, only including destinations established before 1999). **Panel (e):** China's total exports to world (log), disaggregated by firm ownership. **Panel (f):** China's total exports to world (log), disaggregated by trade type.



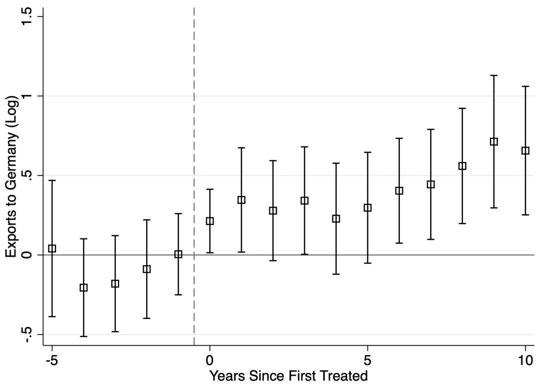
(a) Total Exports to Germany



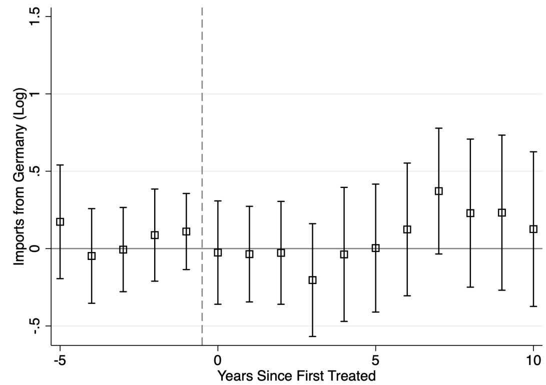
(b) Total Imports from Germany

Figure 5: Product-level Effects on Exports to and Imports from Germany

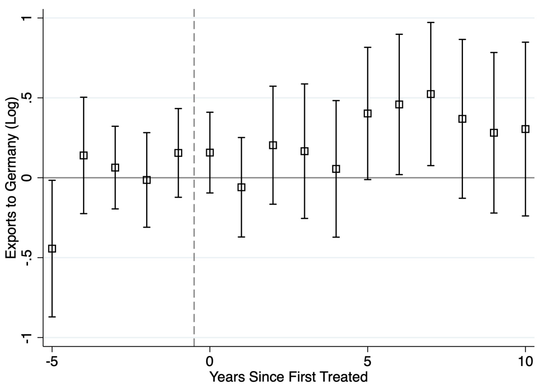
This figure plots the average treatment effects relative to the first year in which each product was introduced in the Guidance. The control group consists of never-treated products within the same industry. Robust standard errors are clustered at the 6-digit product level, and 95% confidence intervals are reported. The dependent variable in **panel (a)** is the log of China's exports to Germany, while the dependent variable in **panel (b)** is the log of China's imports from Germany. Estimates are obtained using the doubly robust difference-in-differences approach proposed by Callaway and Sant'Anna (2021).



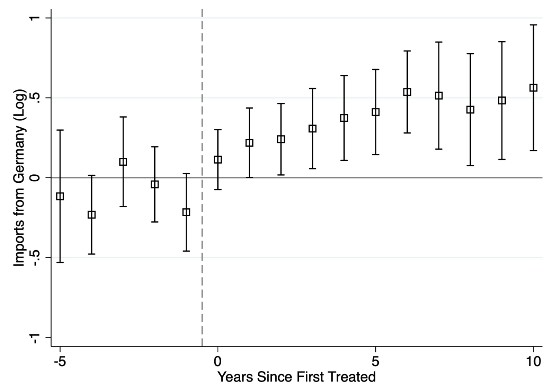
(a) Industrial Supplies: Exports to Germany



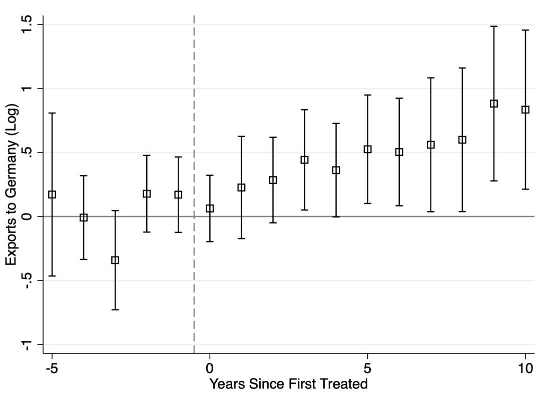
(b) Industrial Supplies: Imports from Germany



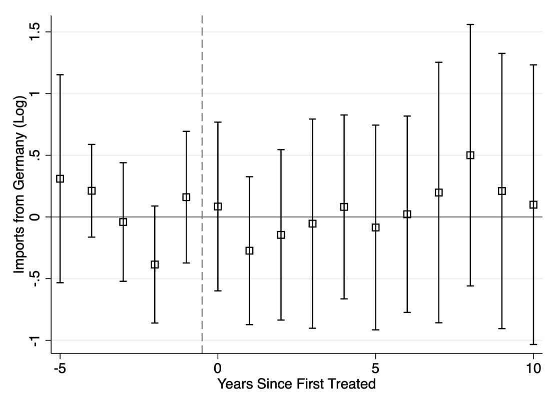
(c) Final Capital Goods: Exports to Germany



(d) Final Capital Goods: Imports from Germany



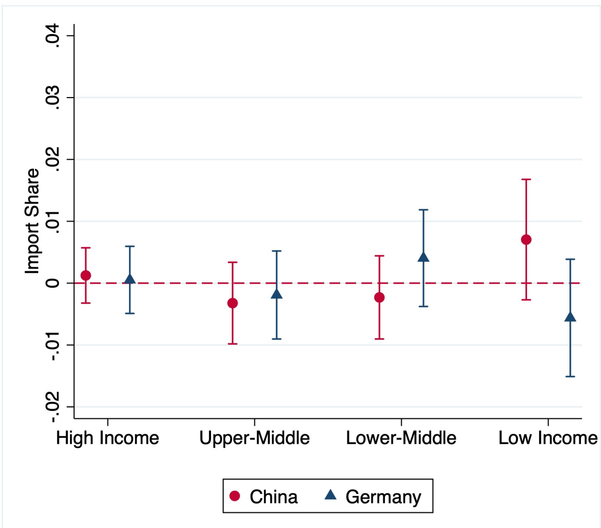
(e) Other Goods: Exports to Germany



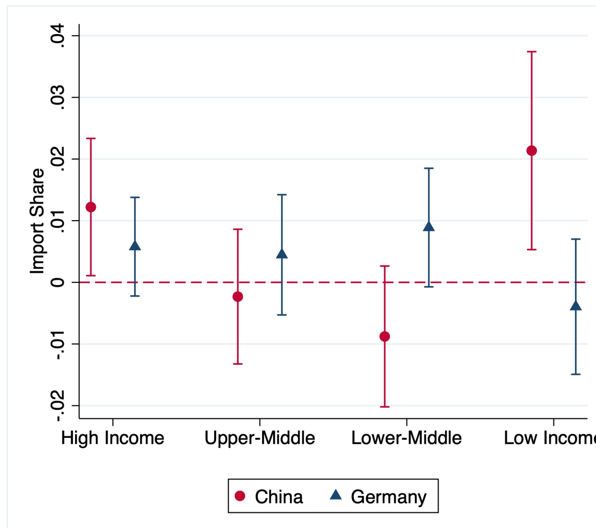
(f) Other Goods: Imports from Germany

Figure 6: Product-level Effects on Exports to and Imports from Germany by Product BEC

This figure plots the average treatment effects relative to the first year in which each product was introduced in the Guidance. The control group consists of never-treated products within the same industry. Robust standard errors are clustered at the 6-digit product level, and 95% confidence intervals are reported. The dependent variable in the left **panels (a)(c)(e)** is the log of China's exports to Germany, with the sample disaggregated by Broad Economic Category (BEC) type, as indicated in the panel titles. The dependent variable in the right **panels (b)(d)(f)** is the log of China's imports from Germany, with the sample specified in the panel titles. Estimates are obtained using the regression-based difference-in-differences approach proposed by Callaway and Sant'Anna (2021).



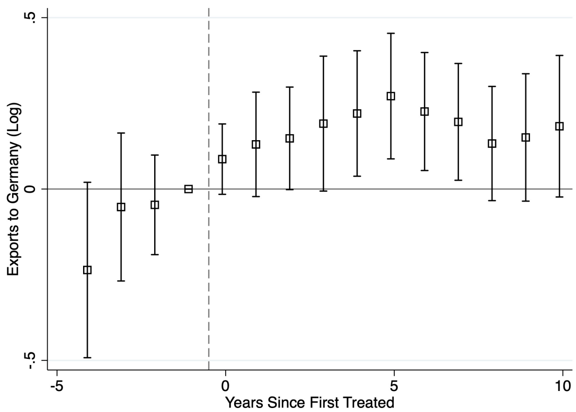
(a) Average ATTs in Year 0-4



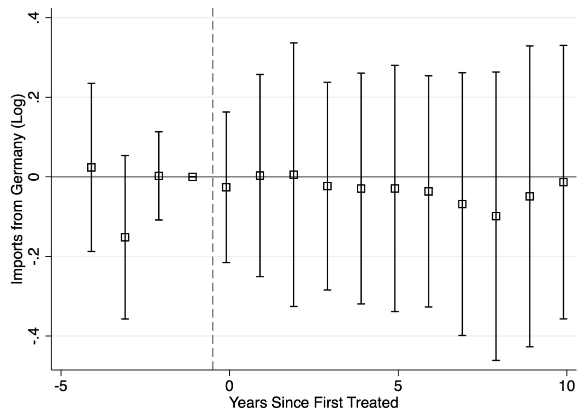
(b) Average ATTs in Year 5-9

Figure 7: Product-level Effects on Global Market Share for Chinese and German Products

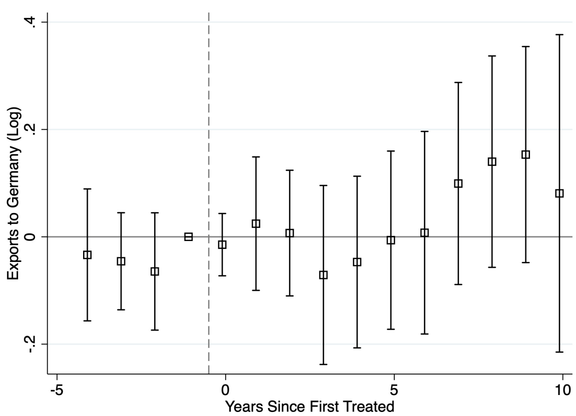
This figure plots the average treatment effects relative to the first year in which each product was introduced in the Guidance. The control group consists of never-treated products within the same industry. Robust standard errors are clustered at the 6-digit product level, and 95% confidence intervals are reported. The dependent variable in the left **panel (a)** is average ATT in the first five-year window following the treatment. The dependent variable in the right **panel (b)** is average ATT in the second five-year window. Importer countries are groupped by income level during 2000-2010, following the World Bank classification into high-income, upper-middle, lower-middle, and low-income groups. Both China and Germany are excluded from these groups. Estimates are obtained using the doubly robust difference-in-differences approach proposed by Callaway and Sant'Anna (2021).



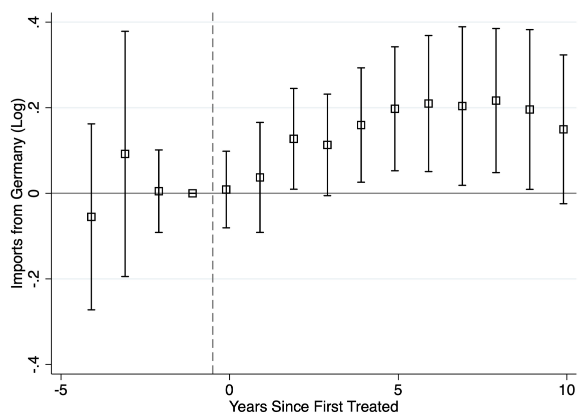
(a) Export to Germany: Downstream



(b) Import from Germany: Downstream



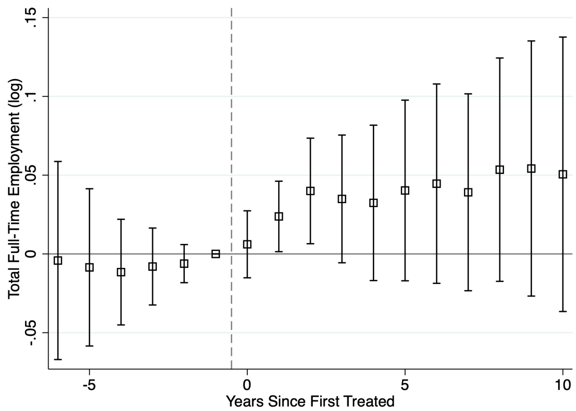
(c) Export to Germany: Upstream



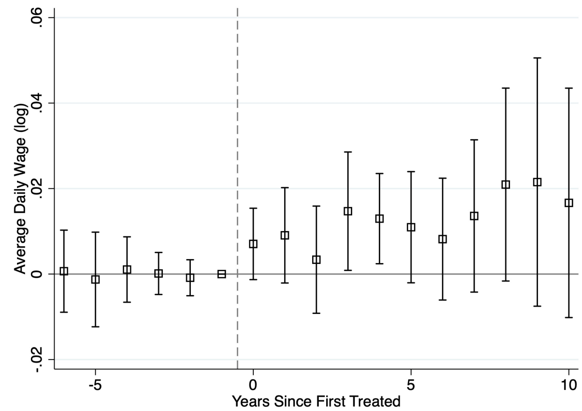
(d) Import from Germany: Upstream

Figure 8: Industry-level Effect on Trade Flows with Germany

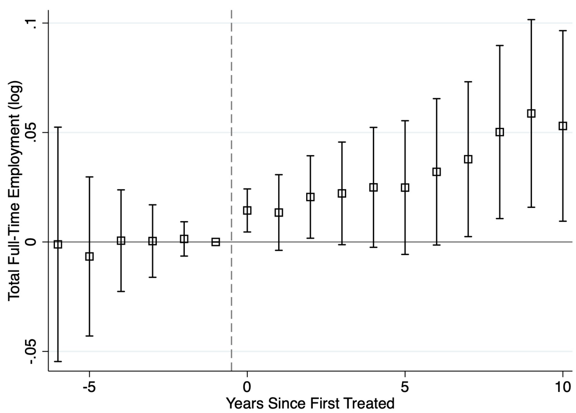
This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable **panels (a)(c)** is the log of China's exports to Germany, while in **panels (b)(d)**, dependent variable is the log of China's imports from Germany. All estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



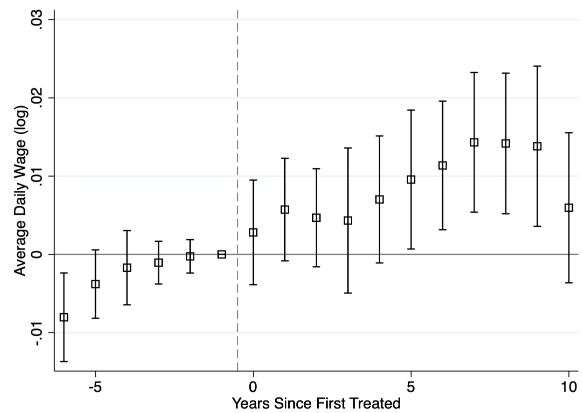
(a) Full-time Employment: Downstream



(b) Average Daily Wage: Downstream



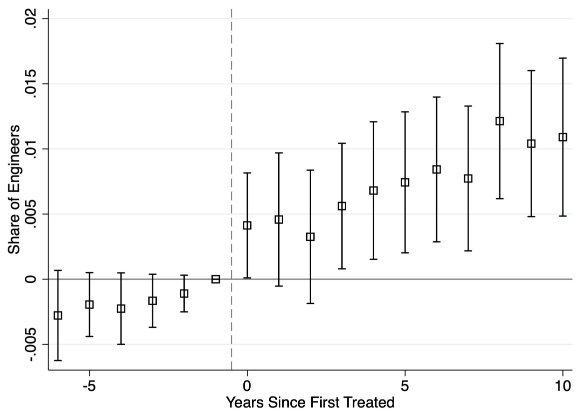
(c) Full-time Employment: Upstream



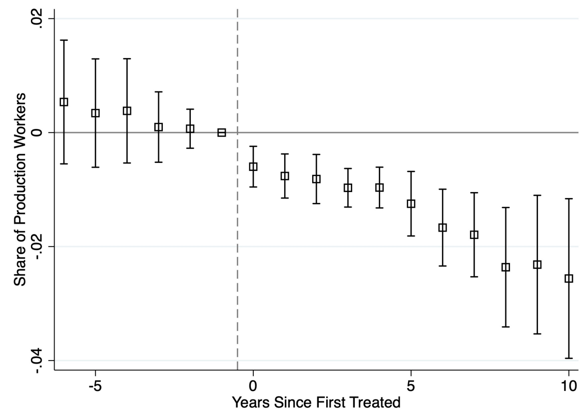
(d) Average Daily Wage: Upstream

Figure 9: Industry-level Effect on German Labour Market: Employment and Wage

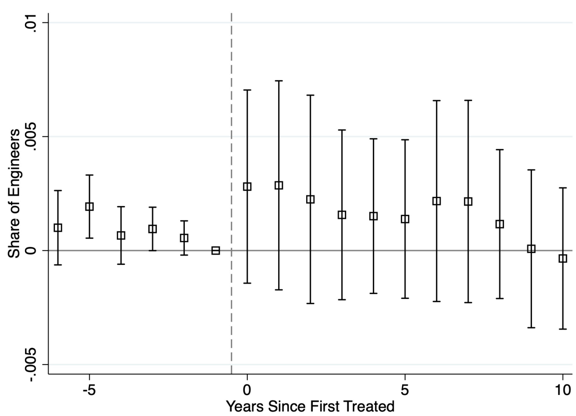
This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in **panels (a)(c)** is the log of total full-time employment of German labour markets, while in **panels (b)(d)** is the log average wage of full-time workers. Estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. All specifications additionally control for pre-treatment average characteristics at the industry level. Observations are weighted by each industry's 1998 employment. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



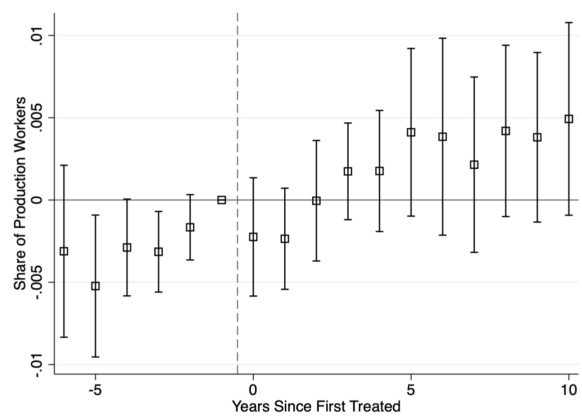
(a) Share of Engineers: Downstream



(b) Share of Production Workers: Downstream



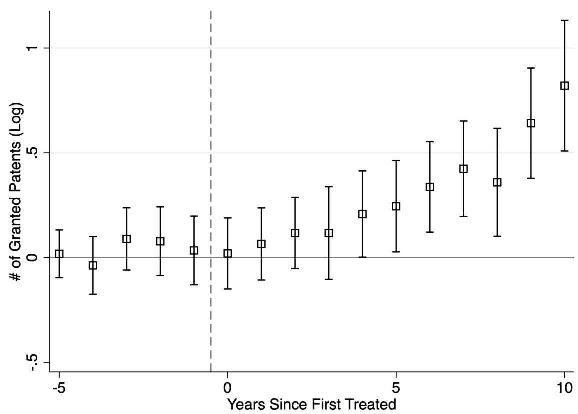
(c) Share of Engineers: Upstream



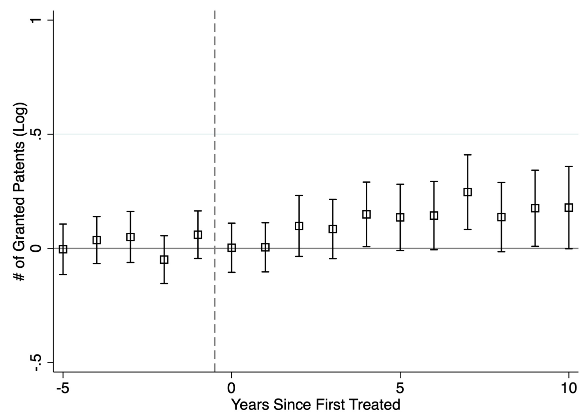
(d) Share of Production Workers: Upstream

Figure 10: Industry-level Effect on German Labour Market: Share of Engineers and Production Workers

This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in **panels (a)(c)** is the share of engineers, while in **panels (b)(d)** is share of production workers. Estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. All specifications additionally control for pre-treatment average characteristics at the industry level. Observations are weighted by each industry's 1998 employment. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



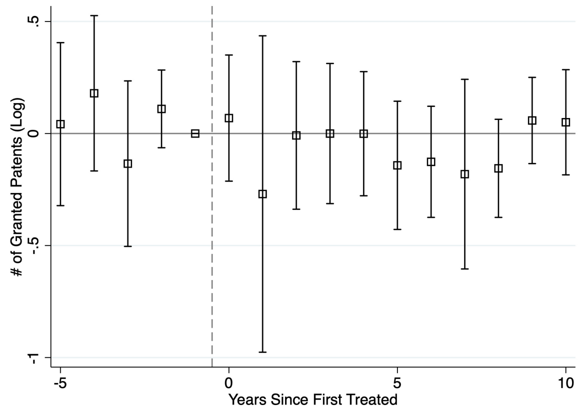
(a) China: Number of Patents



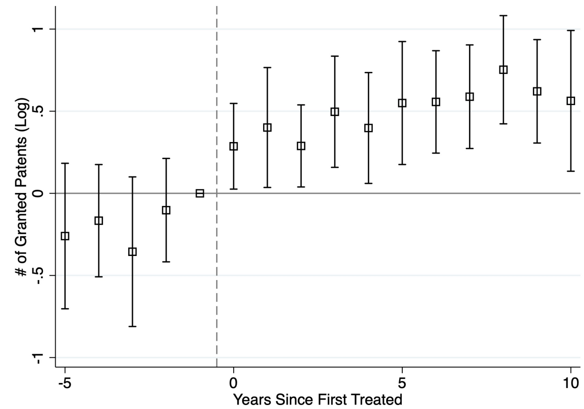
(b) Germany: Number of Patents

Figure 11: IPC-level Effect on Innovation

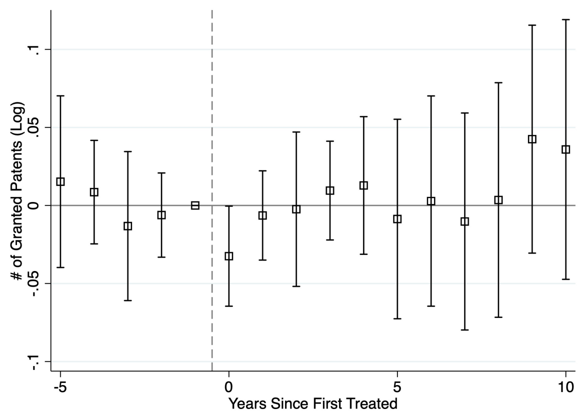
This figure plots average treatment effects relative to the first year in which products associated with each 4-digit IPC code were first introduced in the Guidance. The treatment year for each IPC code is defined based on the earliest Guidance introduction year of its associated products. The control group consists of never-treated IPC codes within the same broad technological category. The dependent variable in **panel (a)** is the log of granted triadic patents filed by Chinese firms and individual inventors; **panel (b)** reports the same outcome for German inventors. The log transformation of patent counts accounts for zeros following Chen and Roth (2024), assigning $log(x) = -1$ when $x = 0$. Estimates are obtained using the doubly robust difference-in-differences approach proposed by Callaway and Sant'Anna (2021). Robust standard errors are clustered at the 4-digit IPC level, and 95% confidence intervals are reported.



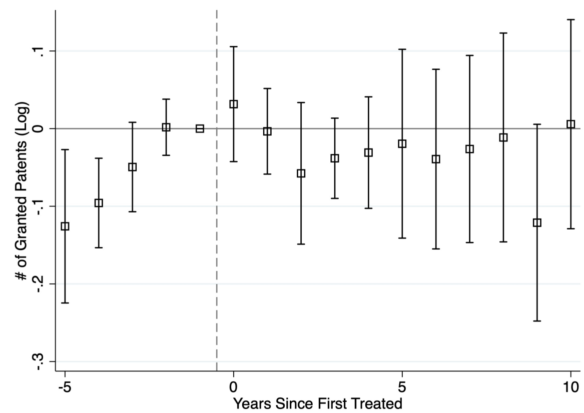
(a) China: Upstream



(b) China: Downstream



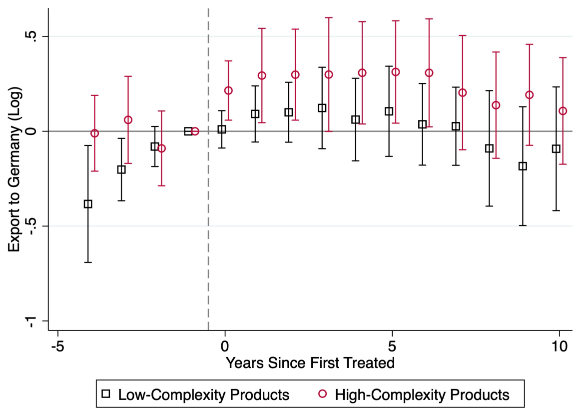
(c) Germany: Upstream



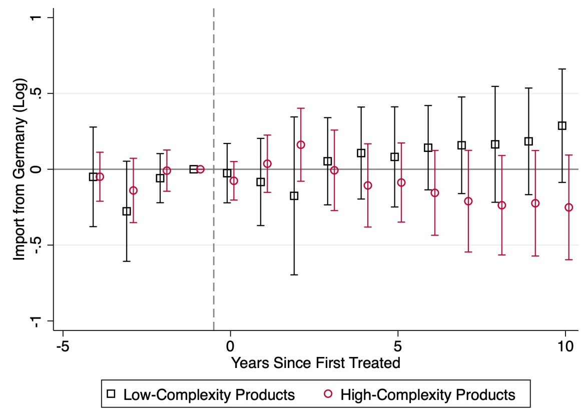
(d) Germany: Downstream

Figure 12: Industry-level Effect on Innovation

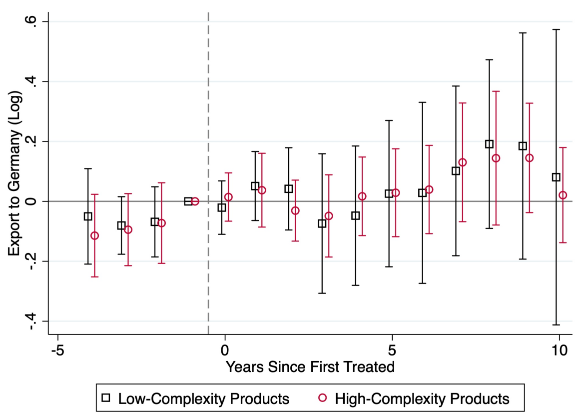
This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in **panels (a)(b)** is the log of granted triadic patents filed by Chinese firms and individual inventors; **panels (c)(d)** report the same outcome for German inventors. Estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. All specifications additionally control for pre-treatment average characteristics at the industry level. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



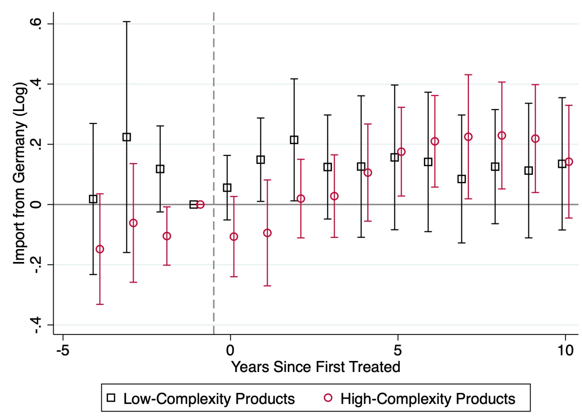
(a) Export to Germany: Downstream



(b) Import from Germany: Downstream



(c) Export to Germany: Upstream



(d) Import from Germany: Upstream

Figure 13: Industry-level Effect on Trade Flows with Germany

This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in the left **panels (a)(c)** is the log of China's exports to Germany, while in the right **panels (b)(d)** is the log of China's imports from Germany. All trade flows are decomposed by product complexity into high-complexity and low-complexity, where the complexity of products is based on *The Atlas of Economic Complexity* (Hausmann et al., 2014). All estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.

A Data Appendix

Industrial Policy Data To link these to standardized trade data, I harmonized the list of 1,136 products from *Guidance* and matched each item to the 6-digit level of the Harmonized System (HS) product classification. Because the terminology in the *Guidance* often differs from official HS descriptions, I applied a fuzzy string-matching algorithm based on the Jaccard similarity index to identify potential matches.[9] All matches were manually reviewed and refined to ensure accuracy and classification consistency. The final mapping identifies 368 treated products at the 6-digit HS level.

Trade Data The BACI database is based on UN Comtrade and provides reconciled bilateral trade flows that are adjusted for cost, insurance, and freight (CIF), while accounting for the reliability of reporting countries. I use the HS 1996 classification for the main product-level analysis (1996-2017), while I use HS 1992 classification for the industry-level analysis (1995-2017). Some high-technology products, such as electric vehicles, only receive specific HS codes in later years.

Chinese Customs data covers 1997 to 2014, which reports China's trade values at the 8-digit HS level, disaggregated by firm ownership and trade type. Since it uses different HS revisions across years, I apply the WITS crosswalk to convert all data to the 1996 HS version at the 6-digit level.

Patent Data The OECD Triadic Patent Families database is based on the European Patent Office's (EPO) Worldwide Statistical Patent Database (PATSTAT, Spring 2024). Each patent can have multiple applicants (individual inventors or firms), and approximately 17% of patents are co-filed by applicants from different countries. However, the database does not identify a primary applicant or the home country of multinational firms. To construct a country-specific patent dataset, I retain only those patent families in which all applicants report the same country of residence (e.g., China or Germany).

Patents are often associated with multiple technological fields, classified using 4-digit International Patent Classification (IPC) codes. I treat each patent-IPC combination as a separate observation. For instance, a patent linked to four IPC codes is counted once under each code. I then aggregate these data to construct a country-IPC-year panel, based on the applicants' country of residence, IPC code, and the earliest filing year.

I map 4-digit IPC codes to ISIC Rev. 3 industry classifications, which are then harmonized to the broader industry level used in the main analysis. Each IPC-ISIC match is assigned a probability weight, reflecting the likelihood that a given patent in a specific IPC is associated with a particular ISIC industry. The aggregated industry-level patent counts are constructed as the weighted sum of patent counts at the IPC level, where each count is weighted by the corresponding IPC-ISIC linkage probability.

[9] To improve matching accuracy, I used detailed product descriptions at the 10-digit HS level for comparison.

Revealed Comparative Advantage (CDK) Index Following Costinot et al. (2012), I estimate the following specification using non-zero export observations at the HS 6-digit product level[10]: $ln(x_{ijp}) = \delta_{ij} + \delta_{jp} + \delta_{ip} + \epsilon_{ijp}$, where x_{ijp} is the exports of product p from exporter i to importer j; δ_{ij} indicates the exporter-importer fixed effects; δ_{jp} and δ_{ip} indicate importer-product fixed effects and exporter-product fixed effects, respectively. After controlling for demand-side components (δ_{jp}), bilateral trade costs and relationships between the importer and exporter (δ_{ij}), the exporter-product productivity is given by $\hat{z}_{ip} = exp(\delta_{ip}/\hat{\theta})$, where the trade elasticity $\hat{\theta}$ is taken from Costinot et al. (2012). I follow Leromain and Orefice (2014) to construct the productivity-based revealed comparative advantage index (hereafter, the CDK index) as the ratio of China's productivity in product p relative to the world average:

$$CDK_{China,p} = \frac{\hat{z}_{China,p}/\bar{\hat{z}}_{China}}{\bar{\hat{z}}_{World,p}/\bar{\hat{z}}_{World}}$$

where $\bar{\hat{z}}_i$, $i \in \{China, World\}$ represents the average exporter-productivity across all products for exporter i; and $\bar{\hat{z}}_{World,p}$ represents the average exporter-productivity across all exporters in product p. Unlike Costinot et al. (2012) who normalize producitivty relative to the United States, this approach benchmarks China's productivity to the world average. A higher value of CDK index therefore indicates that China is relatively more productive in product p compared with the world average, suggesting stronger revealed comparative advantage.

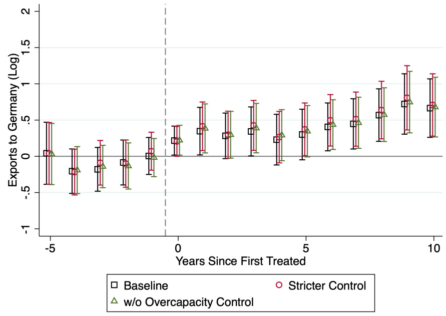
Proxy for Product Quality The BACI-CEPII database reports both trade values and trade quantities. Unit export prices are computed as the ratio of export value to export quantity within each 6-digit product. Since the unit of quantity varies across products, I use within-product log changes in unit prices as a proxy for relative quality upgrading[11].

In addition, I calculate the export-value-weighted average GDP per capita of all destination countries with non-missing GDP per capita data, using the Global Macro Database (Müller et al., 2025). This measure captures the average income level of export markets for each product-year.

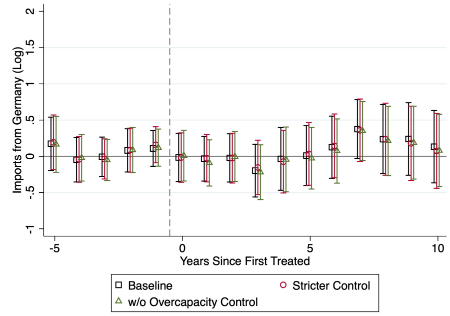
[10] In the whole sample, about 2.5% product-year export flows are zero and are excluded from the estimation.

[11] The DiD estimators of log unit price reflect the log change in unit price between year t and the year before the treatment

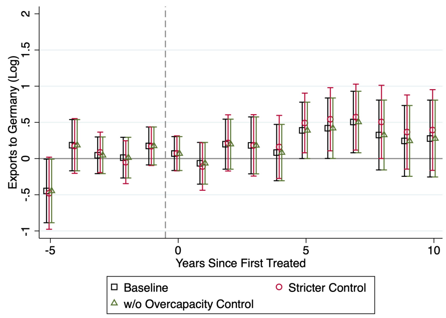
B Figure Appendix



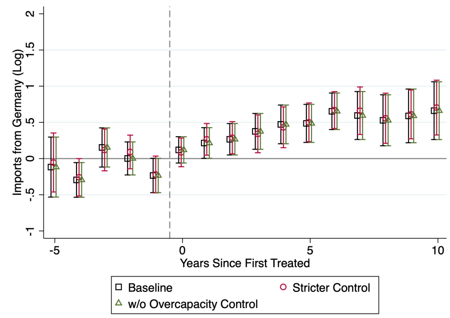
(a) Industrial Supplies: Exports to Germany



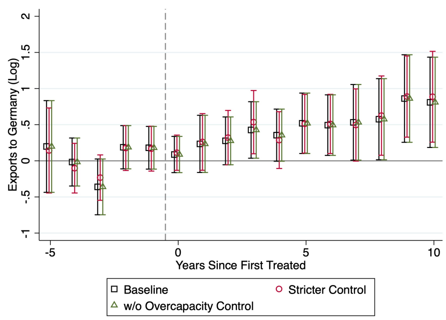
(b) Industrial Supplies: Imports from Germany



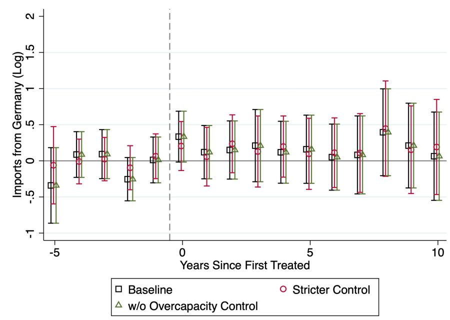
(c) Final Capital Goods: Exports to Germany



(d) Final Capital Goods: Imports from Germany



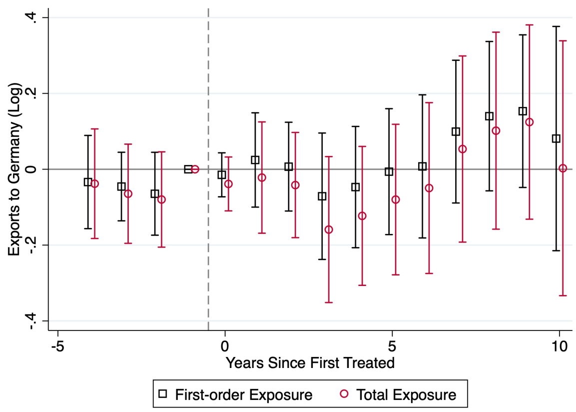
(e) Other Goods: Exports to Germany



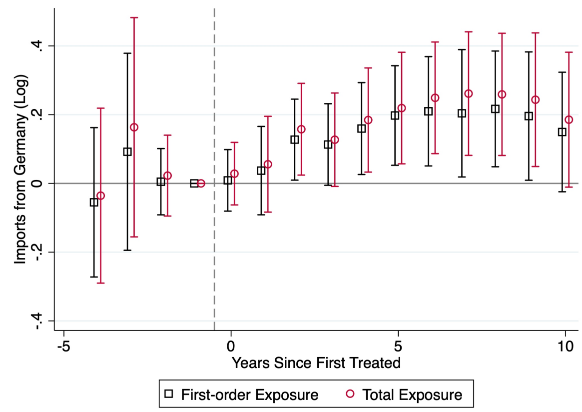
(f) Other Goods: Imports from Germany

Figure 14: Robustness: Product-level Effects on Exports to and Imports from Germany by Product BEC

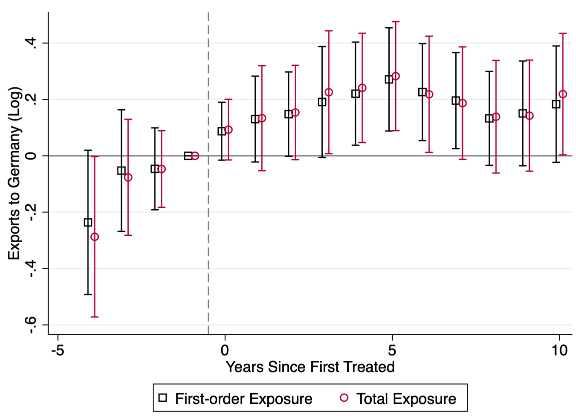
This figure plots the average treatment effects relative to the first year in which each product was introduced in the Guidance. The control group varies across specifications: the baseline includes never-treated products within the same industry; alternative specifications exclude products targeted by other high-tech IPs or affected by capacity control policies. Other settings are the same as in Figure 6.



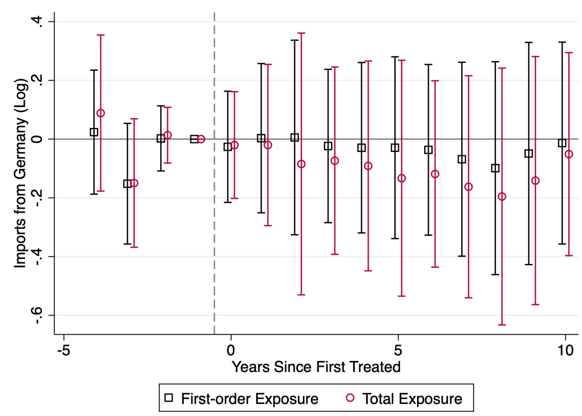
(a) Export to Germany: Upstream Exposure



(b) Import from Germany: Upstream Exposure



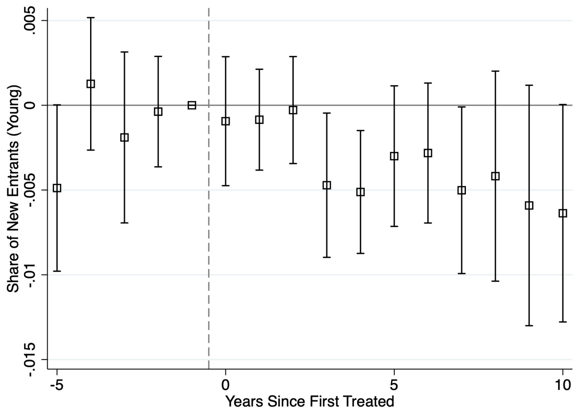
(c) Export to Germany: Downstream Exposure



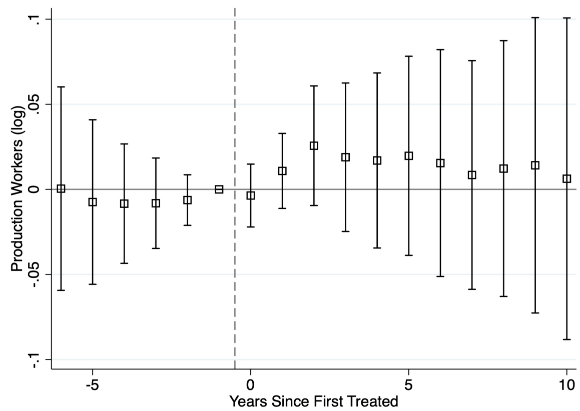
(d) Import from Germany: Downstream Exposure

Figure 15: Robustness: Industry-level Effect on Trade Flows with Germany

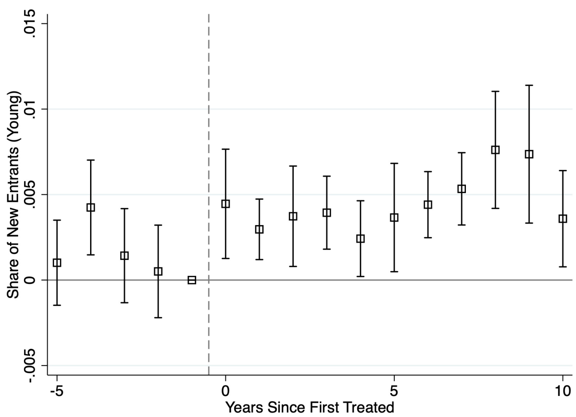
This figure presents the estimated effects of China's industrial policoes using a continuous-treatment difference-in-differences framework at the industry level. Stricter control plots estimations using the control group that excluding industries under other policies. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. Total exposure includes full exposure that derived from the Leontief Matrix. *Upstream exposure* reflects spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures spillovers through its role as a buyer of inputs from treated industries. The dependent variable in the left **panels (a)(c)** is the log of China's exports to Germany, while in the right **panels (b)(d)** is the log of China's imports from Germany. All estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



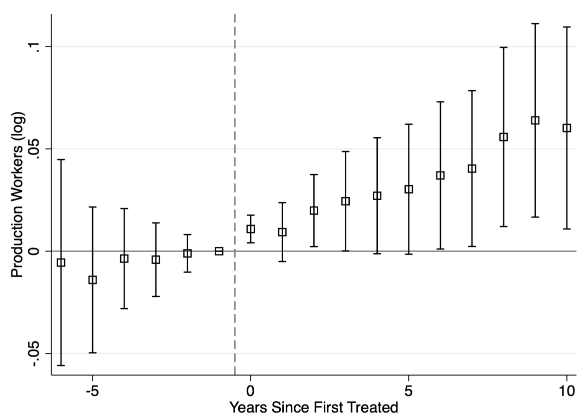
(a) Share of New Entrants (under 30): Downstream



(b) Production Workers (log): Downstream



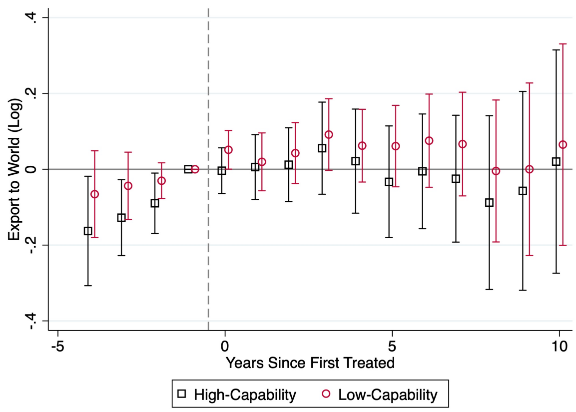
(c) Share of New Entrants (under 30): Upstream



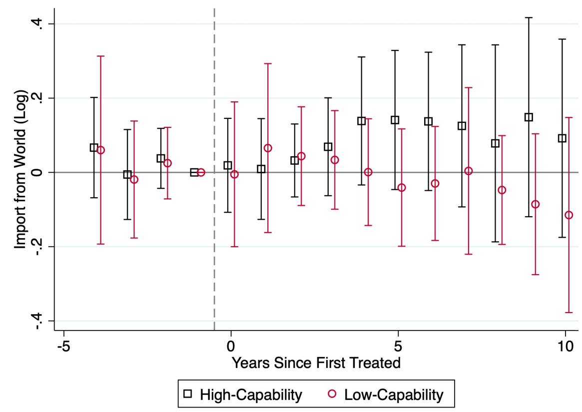
(d) Production Workers (log): Upstream

Figure 16: Industry-level Effect on German Labour Market: Share of Engineers and Production Workers

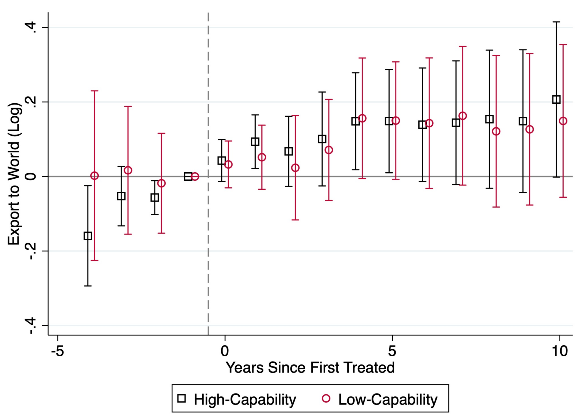
This figure presents the estimated effects of China's industrial policies using a continuous-treatment difference-in-differences framework at the industry level. Treatment intensity is defined by the measure indicated in each panel title, with all continuous treatment variables standardized by their sample standard deviations. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries, while *downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in **panels (a)(c)** is the share of new entrants under 30, calculated by the total number of workers under 30 that first worked in the industry j in year t over industry j's 1998 employment. Dependent variable in **panels (b)(d)** is log of production workers. Estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. All specifications additionally control for pre-treatment average characteristics at the industry level. Observations are weighted by each industry's 1998 employment. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



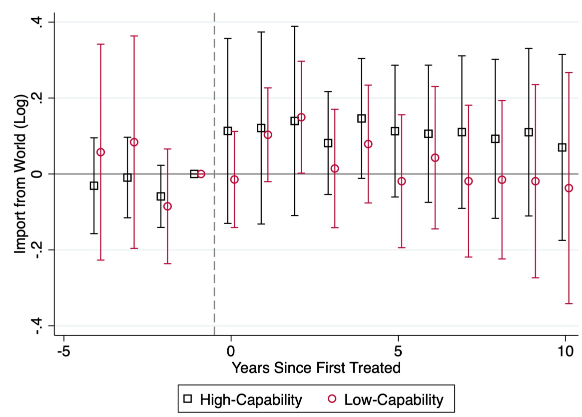
(a) Low-Complexity Export to World: Downstream



(b) Low-Complexity Import from World: Downstream



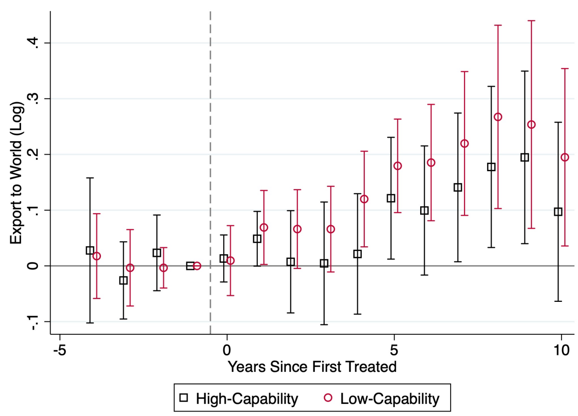
(c) High-Complexity Export to World: Downstream



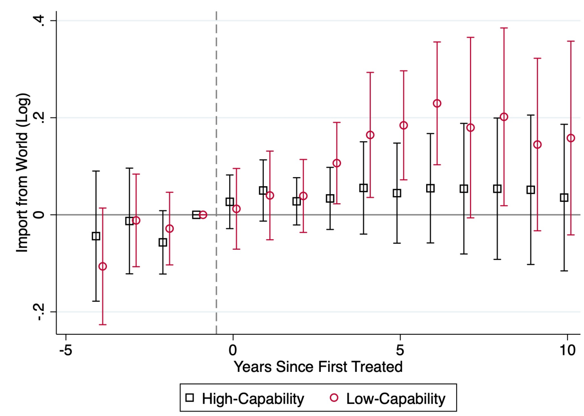
(d) High-Complexity Import from World: Downstream

Figure 17: Industry-level Effect on Trade Flows with RoW: Downstream

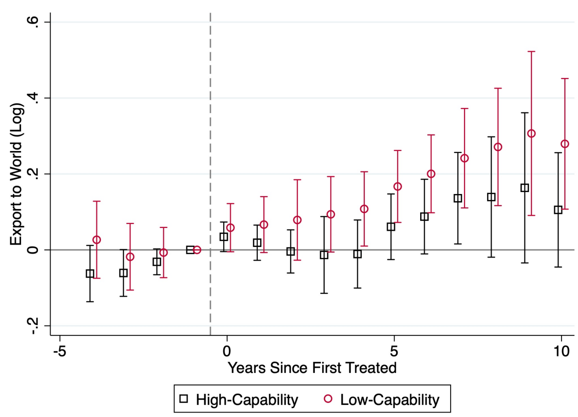
This figure plots the estimated effects of China's industrial policies using a continuous treatment difference-in-differences framework at the industry level. The treatment intensity is defined by the measure indicated in each panel title, and all continuous treatment variables are standardized by their sample standard deviation. *Downstream exposure* captures first-order spillovers through its role as a buyer of inputs from treated industries. The dependent variable in the left **panels (a)(c)** is the log of China's exports to the rest of world, while in the right **panels (b)(d)** is the log of China's imports from the rest of world. All trade flows are decomposed by product and complexity, where the complexity of products is based on *The Atlas of Economic Complexity* (Hausmann et al., 2014). All estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.



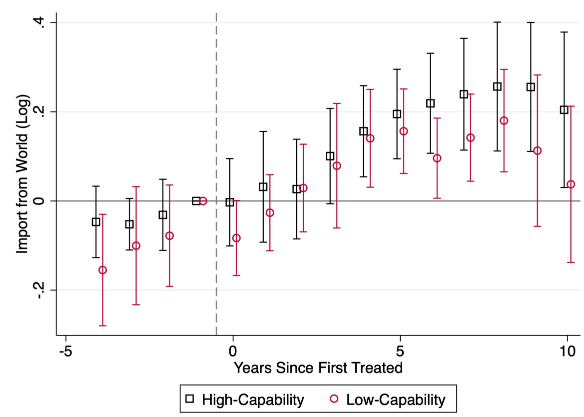
(a) Low-Complexity Export to World: Upstream



(b) Low-Complexity Import from World: Upstream



(c) High-Complexity Export to World: Upstream



(d) High-Complexity Import from World: Upstream

Figure 18: Industry-level Effect on Trade Flows with RoW: Upstream

This figure plots the estimated effects of China's industrial policies using a continuous treatment difference-in-differences framework at the industry level. The treatment intensity is defined by the measure indicated in each panel title, and all continuous treatment variables are standardized by their sample standard deviation. *Upstream exposure* reflects first-order spillovers through an industry's role as a supplier to treated industries The dependent variable in the left **panels (a)(c)** is the log of China's exports to the rest of world, while in the right **panels (b)(d)** is the log of China's imports from the rest of world. All trade flows are decomposed by product and complexity, where the complexity of products is based on *The Atlas of Economic Complexity* (Hausmann et al., 2014). All estimates are obtained using two-way fixed effects (TWFE) specification, with industry and year fixed effects. Robust standard errors are clustered at the industry level, and 95% confidence intervals are reported.