INTERNATIONAL MONETARY FUND

Industrial Policy in China: Quantification and Impact on Misallocation

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WP/25/155

2025
AUG

WORKING PAPER

 WP/25/155

IMF Working Paper
Asia and the Pacific Department

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Authorized for distribution by Sonali Jain-Chandra
August 2025

ABSTRACT: This paper quantifies the size of the main industrial policy instruments in China and estimates their impact on domestic factor misallocation and aggregate productivity. The quantification of industrial policy instruments leverages data from financial reports of listed firms and the land registry. The equivalent fiscal cost of industrial policy through cash subsidies, tax benefits, subsidized credit, and subsidized land for favored sectors (including both private and state-owned firms) is estimated at about 4 percent of GDP per year, with a growing share of tax benefits over time. Next, the paper uses a structural model to estimate the relationship between industrial policies and factor misallocation for a broad sample of firms. Various industrial policy instruments are found to affect factor allocations in different ways—subsidies tend to lead to excess production, while trade and regulatory barriers limit production. Overall, factor misallocation from industrial policies is estimated to reduce domestic aggregate TFP by about 1.2 percent. The results resonate with IMF policy recommendations for China to scale back industrial policy and increase its transparency.

RECOMMENDED CITATION: Garcia-Macia, Daniel, Siddharth Kothari, and Yifan Tao. 2025. “Industrial Policy in China: Quantification and Impact on Misallocation”, International Monetary Fund Working Paper No. 2025/155.

JEL Classification Numbers:	L52, O47, H25
Keywords:	China; Industrial Policy; Misallocation; Productivity
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* This paper benefited from the guidance of Thomas Helbling, Sonali Jain-Chandra, and Krishna Srinivasan, as well as comments from Yonqquan Cao, Chang-Tai Hsieh, Benjamin Kett, Samuel Pienknagura, Michele Ruta, Lorenzo Rotunno, Robert Zymek, Aleksandra Zdzienicka, and various participants at IMF seminars, and a seminar with the Chinese authorities.. Diego Cerdeiro, Reka Juhasz, Nathan Lane, Emily Oehlsen, and Verónica C. Pérez kindly shared their datasets. Ding Hua and Tommy Lee provided research assistance.
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WORKING PAPERS

Industrial Policy in China: Quantification and Impact on Misallocation

Prepared by Daniel Garcia-Macia, Siddharth Kothari, and Yifan Tao[1]

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1. Introduction

Industrial policies (IP), defined as policies aimed at changing the sectoral structure of the economy, have been widely used around the world, particularly in recent years. In China, IPs have long been a centerpiece of economic policy. The government has used an array of policy tools, including (but not limited to) cash subsidies, tax benefits, subsidized credit, subsidized land, trade and regulatory barriers, and industry coordination to promote certain economic sectors (State Council 2005).[1] This has had a material impact on the economy, helping to develop specific industries and technologies, but also generating fiscal costs and potential factor misallocation. However, official information on the size of IP support or the effects of such policies is for the most part unavailable.

This paper aims to shed light on these two issues. First, it quantifies the size of the main IP instruments in China using data from financial reports of listed firms and the land registry. Second, it estimates the impact of IP on domestic factor misallocation and aggregate productivity using a structural model.

The first part of the paper uses data over the 2010-23 period from financial statements of listed firms from WIND, as well as the land registry, to calculate the equivalent fiscal cost of four IP instruments, namely cash subsidies, tax benefits, subsidized credit, and subsidized land for favored sectors. Cash subsidies are directly reported by firms, while tax benefits are measured as the gap between the statutory tax rate and effective corporate income tax rates computed from financial statements at the sector level. Credit subsidies are identified as the difference in effective interest rates for firms in the manufacturing sector versus other sectors, after controlling for other financial variables at the firm level and firm type. Finally, land subsidies are estimated using the land registry, which covers the universe of land sales (about 1.6 million transactions). The estimation compares the unit prices of land sold by the government to manufacturing firms with the prices for nearby firms (within a one-kilometer radius) in other sectors and the same year.

The main result of this analysis is that the equivalent fiscal cost of IP in China is estimated at 4.4 percent of GDP as of 2023. The largest instrument is cash subsidies (at 2.0 percent of GDP), followed by tax benefits (1.5 percent), land subsidies (0.5 percent), and subsidized credit (0.4 percent). The total size of IP has been broadly stable over time, although tax subsidies have grown in importance in the aftermath of the pandemic, while the use of other instruments has slightly diminished. State-owned enterprises (SOEs) tend to benefit from lower interest rates and higher cash subsidy rates (after controlling for the sector of activity), but tax benefits are higher for private firms, and private firms are dominant in the sectors favored by IP, suggesting that IP goes well beyond SOE support.

The second part of the paper leverages a measure of IP counts from Juhasz et al. (2025) and relates it to factor misallocation and aggregate productivity, which are measured using the Hsieh and Klenow (2009) model and data from Orbis and KLEMS. Specifically, the analysis estimates the cumulative effect of IP policies implemented between 2009 and 2018 on sector-level misallocation outcomes in 2018, with the choice of time period driven by data availability. Then, it uses the model to approximate the impact of IP on aggregate total factor productivity (TFP) through changes in allocative efficiency. This approach relies on stronger structural

[1] The Interim Provisions on Promoting Industrial Structure Adjustment (State Council 2005) note that “All relevant administrative departments shall speed up the formulation and amendment of policies on public finance, taxation, credit, land, import and export, etc., effectively intensify the coordination and cooperation with industrial policies, and further improve and promote the policy system on industrial structure adjustment.”

assumptions than the quantification of IP in the first part of the paper, but covers a wider sample of firms and IP tools—including trade and regulatory barriers—and captures general equilibrium effects.

The estimation results show that IP affects the allocation of production factors, but the different instruments do so in opposite ways. Subsidies are associated with excess production relative to a no-distortions benchmark, while trade and regulatory barriers limit production, possibly by increasing the market power of incumbents. Overall, factor misallocation from IP is estimated to reduce domestic aggregate TFP by about 1.2 percent relative to a no IP baseline, and this channel could reduce the level of GDP by up to 2 percent. The analysis also suggests that industrial champions, or market-leading firms, owe their position to both higher productivity and policies encouraging their production relative to the average firm in the sector.

This paper focuses on the fiscal cost of IP and implications for domestic factor misallocation, while abstracting from the potential benefits of IP such as correcting market failures, including knowledge spillovers, which could in principle lead to positive TFP or welfare effects. That said, the analysis does not find evidence that sector-level IP intensity significantly affects average firm-level TFP in the same sector. Negative effects of IP such as decreased competition in a sector or within-firm factor misallocation may be offsetting its potential benefits on firm-level productivity. The paper also abstracts from the international spillovers of China's IP.[2]

Most of the literature on IP in China has focused on advantages to SOEs (Song et al. 2011, Brandt et al. 2013, Lam and Schipke 2016, Gatley 2019, Jurzyk and Ruane 2021, Di Pippo et al. 2022, IIF 2025) or individual policy instruments or sectors (Barwick et al. 2023 and 2024, Goldberg et al. 2024, World Bank 2024, Xu 2024). This paper contributes to this literature by defining IP based on sector-level support, in line with the standard definition of IP in the international literature (Juhasz et al. 2023), and providing a comprehensive estimate of the size of IP across various instruments for the whole economy. By estimating the economic size of IP, the paper also complements recent work by Fang et al. (2025), which measures IP policy counts in China. Finally, the paper is closely linked to the literature on factor misallocation (e.g., Hsieh and Klenow 2009, Restuccia and Rogerson 2017). It expands on earlier results that IP is linked to within-sector misallocation in China (Chen et al. 2022) by using more granular sectoral data on IP intensity and estimating impacts on misallocation between sectors, which are found to be substantially larger than impacts on misallocation within sectors.

The rest of the paper is organized as follows. Section 2 describes the quantification of IP instruments. Section 3 presents the structural estimation of the impact of industrial policy on misallocation and productivity. Section 4 concludes with policy takeaways.

2. Quantification of Industrial Policy

The quantification of IP in this section covers four instruments for which data are available: cash subsidies, tax benefits, subsidized credit, and subsidized land. For the first three instruments, it uses financial statements of listed firms from WIND, covering more than 5,000 listed firms over the 2010-23 period. Land subsidies are estimated with land registry data from the Ministry of Natural Resources, which includes the universe of land sales by the government (about 1.6 million transactions), also over 2010-23. The approach and results for each

[2] Both these aspects are covered in the China 2024 Article IV Report, leveraging research from Garcia-Macia and Sollaci (2024) on knowledge spillovers of IP and from Rotunno and Ruta (2024) on international spillovers. See Baquie et al. (2025) for other potential benefits of IP.

instrument are described below. Annex I provides a more detailed description of the data sources and summary statistics for the key variables.

Cash Subsidies

Cash subsidies are the most straightforward instrument to measure, since they are reported as a separate item in the income statements of listed firms. Figure 1.1 shows the subsidy rate defined as aggregate cash subsidies as a share of value added by sector,[3] highlighting the top and bottom thirds of sectors (out of 21 “industry groups” in WIND). Among the most subsidized sectors are those that are often identified as a priority by the authorities (e.g., National People's Congress 2021), including semiconductors, high-tech manufacturing, and automobiles, while the least favored sectors include consumer goods, services, real estate, and energy. Overall, aggregate subsidy rates have declined over the last decade, from 2.4 percent in 2013 to 2.0 percent in 2023, but the sectoral ranking has been remarkably stable.

Figure 2.1 displays the evolution of subsidy rates by firm type, distinguishing between SOEs and privately-owned enterprises (POEs). For most of the period, POEs have higher subsidy rates, except during the 2015 downturn, which triggered a large push in SOE investment. However, this is driven by the larger share of POEs in favored sectors. After controlling for the sector of the firm, the average subsidy rate tends to be 0.7 percentage points higher for SOEs on average—a statistically significant difference.

Tax Benefits

Tax benefits at the sector level are measured as the gap between the corporate income tax top statutory rate of 25 percent and the effective corporate income tax rate for the sector. The latter is measured in WIND as corporate income tax payments over total earnings before taxes in a given year.[4] This is a broad measure that captures various benefits, including asset-specific investment incentives or tax discounts for firms in special economic zones, to the extent their incidence varies across sectors.[5]

Figure 1.2 displays the estimated corporate income tax benefits as a share of profits by sector. Tellingly, the ranking of sectors is highly correlated with the one for cash subsidies in Figure 1.1, with 6 out of 7 sectors at both the top and bottom thirds for taxes also featuring at the top and bottom for cash subsidies, respectively. The evolution over time is different, though, with aggregate tax benefit rates increasing from 4.4 percent in 2013 to 6.3 percent in 2023. While effective tax rates can capture many factors, the fact that the estimates are close to zero or even negative for some sectors provides some reassurance that there is no systematic overstatement. Moreover, effective tax rates would be even lower if deferred tax expenses were excluded, as is common in the literature (Zhang et al. 2016), which would result in a higher estimated tax benefit. Finally, the analysis does not cover other taxes with rates that vary across sectors, such as value added taxes and social security contributions, which would add up to the tally of IP tax benefits.

[3] Value added is not available in WIND. It is constructed as revenues minus operating costs net of labor costs, where labor costs are approximated as the firm’s labor count times urban wages from the NBS, following David and Venkateswaran (2019), and rescaled to match the aggregate labor share in KLEMS. Only firms with strictly positive value added are included.

[4] Defining effective benefits as a share of average profits in the current and previous years delivers similar results.

[5] The analysis of average effective tax rates complements studies of marginal effective tax rates by asset type or sector (e.g., Brollo et al. 2024), as it allows to calculate the total fiscal cost.

Figure 1.1. Cash Subsidies
(percent of value added)

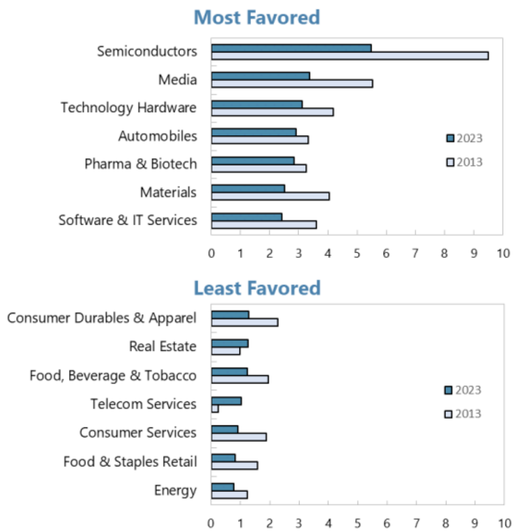
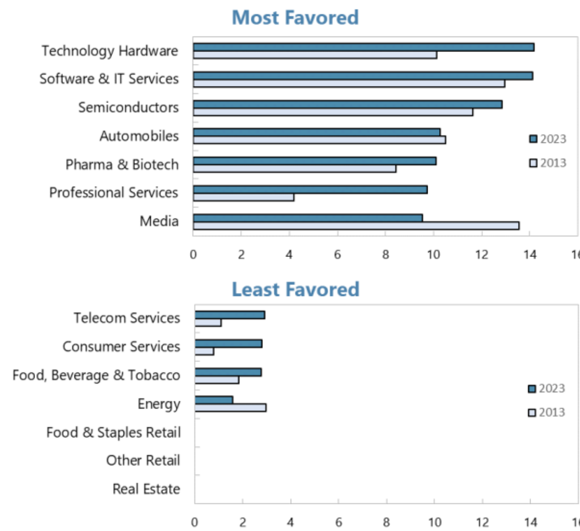


Figure 1.2. Corporate Income Tax Benefits
(percent of profits)



Sources: Wind and Staff calculations.
Note: Sectors are classified into 21 categories, following the WIND "industry group" definition. Shares are calculated at the sector level. The sample only includes listed firms and excludes financial firms and firms with negative value added. In the RHS chart, CIT benefits are calculated as the difference between the CIT statutory tax rate of 25 percent and the effective CIT rate, defined as CIT taxes over profits. Firms with non-positive profits or income tax payments are excluded. Sectors with negative tax benefits are truncated at zero.

Figure 2.1. Cash Subsidies
(percent of value added)

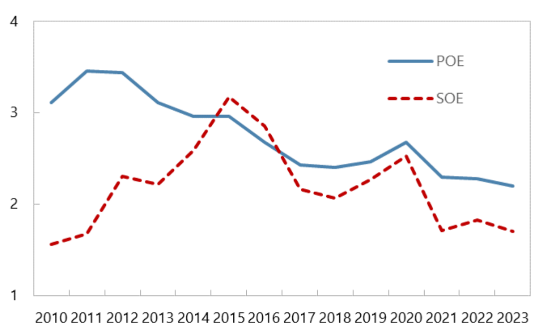
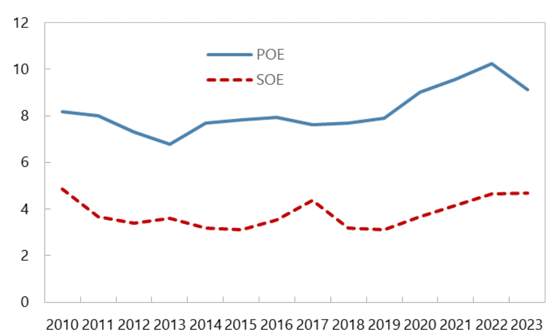


Figure 2.2. Corporate Income Tax Benefits
(percent of profits)



Sources: Wind and Staff calculations.
Note: POE = privately-owned enterprises, SOE = state-owned enterprises. The sample only includes listed firms, and excludes financial firms and firms with negative value added. In the RHS chart, CIT benefits are calculated as the difference between the CIT statutory tax rate of 25 percent and the effective CIT rate, defined as CIT taxes over profits. Firms with non-positive profits or income tax payments are excluded.

As is the case for cash subsidies, POEs receive larger tax benefits as a percent of profits than SOEs, with a gap that has somewhat widened in recent years (Figure 2.2). In the case of tax benefits, though, the sectoral distribution only explains about half of the POE advantage. Possible explanations include SOEs featuring stronger tax compliance than POEs, and tax incentives being less necessary to align SOE production decisions with government goals.

Subsidized Credit

Credit subsidies are measured as differences in effective interest rates across sectors that are not explained by standard financial determinants and other control variables. In particular, the following regression equation is estimated at the firm level:

$$r_{i,t} = \alpha + \boldsymbol{\beta} * \boldsymbol{s_i} + \boldsymbol{\gamma} * \boldsymbol{z_{i,t}} + \tau_t + \varepsilon_{i,t} \text{ ,}$$

where i indexes the firm, t the year, r is the effective nominal interest rate defined as interest payments divided by interest bearing liabilities in the previous year as measured in WIND, $\boldsymbol{s}$ is a vector of categorical variables indicating the sector of the firm (with different sectoral groupings depending on the specification), $\boldsymbol{z}$ a vector of control variables, τ are year fixed effects, and ε is an independent error term (potentially correlated within a sector and across time). The other Greek letters denote coefficients. Bold variables denote vectors. The control variables $\boldsymbol{z}$ include firm type—with dummies for central SOEs, local SOEs, foreign firms, and POEs (the excluded group), firm leverage, asset size (in logs), the share of short-term debt over total debt, and the share of intangible assets over total assets. All financial control variables are lagged.

Table 1 reports the coefficient estimates for various specifications. The first specification (column 1) estimates whether the most and least favored sectors according to both cash subsidies and tax benefits (the 6 sectors at the top and bottom of both Figures 1.1 and 1.2, respectively) also benefit from lower and higher interest rates, respectively. While the most favored sectors do benefit from a lower effective interest rate, the coefficient for the least favored sectors is not statistically significant, and both coefficients are economically small. Hence, a second specification is run to test differences for the manufacturing sector as a whole. In this case, the result is significant: manufacturing firms tend to benefit from effective interest rates that are 0.4 percentage points below those of other sectors (column 2). This second specification is henceforth used as the benchmark.

The regression also shows that SOEs, and particularly central SOEs, tend to benefit from lower rates than POEs, consistent with previous literature (e.g., Gatley 2019, Zhang et al. 2019, Jurzyk and Ruane 2021, Di Pippo et al. 2023). This may reflect lower perceived risk due to government implicit guarantees. As expected, larger firms and firms with a lower share of intangible assets also tend to benefit from lower rates, although the latter is not significant. Somewhat surprisingly, though, higher leverage and more long-term debt are associated with lower rates, which might reflect SOE banks (which account for more than half of bank assets) assisting higher-risk firms in rolling over their debt.

The main result that manufacturing firms receive lower rates is robust to a) excluding the firm-type variable, b) adding controls for profitability (the lagged return on assets of the firm, as well as the industry-level price-to-earnings ratio, which should capture industry growth prospects), c) defining effective interest rates with current (instead of lagged) interest bearing liabilities in the denominator (columns 3 to 5 in Table 1), and d) adding a proxy for industry riskiness, measured by the average absolute yearly change in firm-level profits as a share of assets, as a regressor (the coefficient on the proxy for risk is not statistically significant). However, the estimated discount for manufacturing firms becomes smaller and statistically insignificant when financial controls are removed (not shown), highlighting the importance of controlling for those factors.

A similar specification is used to test whether manufacturing firms tend to have more zero-interest net accounts payable, which has been highlighted as a form of credit support to SOEs in the literature (Gatley 2019, Di Pippo et al. 2022), but no statistically significance difference is found (not shown).

Table 1. Effective Interest Rates by Sector—Regression Results

Dependent Variable: **Effective interest rate** (percent)	**sectors by subsidies and tax benefits**	**main specification**	**no firm type control**	**profitability controls**	**denominator not lagged**
Most favored (rel. to other sectors)	-0.23**				
Least favored (rel. to other sectors)	-0.17				
Manufacturing (rel. to other sectors)		-0.43***	-0.4***	-0.42***	-0.32***
Central SOE	-0.55***	-0.58***		-0.62***	-0.06
Local SOE	-0.19**	-0.24**		-0.25***	0.05
Foreign Firm	-0.39**	-0.38**		-0.39**	-0.02
Debt/Assets (lag)	-0.01**	-0.01**	-0.01**	-0.02**	0.02***
Log Assets (lag)	-0.13***	-0.14***	-0.19***	-0.12***	-0.28***
Short-Term Debt Share (lag)	1.02***	1.04***	1.06***	0.93***	1.04***
Intangible Asset Share (lag)	0.6	0.37	0.41	0.4	0.25
Return on Assets (lag)				-1.83***	
Industry Price-to-Earnings (lag)				0.00	
R^2	0.05	0.05	0.05	0.06	0.05
Num. of observations	32159	32159	32159	32159	31811

Sources: Wind and Staff calculations.
Note: Firm-level pooled OLS regression for listed firms from 2010-23, including year fixed effects. The excluded categories are other sectors and POEs. The sample only includes listed firms, and excludes financial and real estate firms, firms with negative value added, and observations with effective interest rates outside the 0 to 25 percent interval. Asterisks indicate p-values below 1, 5, and 10 percent, respectively, with standard errors clustered at the sector level.

Subsidized Land

Next, land subsidies are estimated using the land registry data. Consistent with the approach for other IP instruments, the estimation is based on sector-level differences in land prices. The analysis compares the unit price of land sold by the government to manufacturing firms versus the price of land sold to firms in non-manufacturing market-based sectors (i.e., excluding land for public uses), after controlling for unrelated factors.

It is well documented that in China industrial land is on average substantially cheaper than land for other uses, but comparisons of average prices may conflate factors related to the location of the land. Hence, this section leverages information on the geographical coordinates of each land transaction available in the registry to analyze price differences between transactions occurring within a small distance and in the same year. This is inspired in the “ring method” common in urban economics (Butts 2023) and constitutes an innovation relative to previous estimates of IP land subsidies based on less granular price indices (Lam and Schipke 2016, Di Pippo et al. 2022, IIF 2025).

For each land sale transaction in manufacturing i in year t with unit price $p_{i,t}$, an equivalent or benchmark price of land transactions in the non-manufacturing sectors is computed. This price, $\hat{p}_{i,t}$, is defined as the average price of nearby transactions in non-manufacturing sectors in the same year:

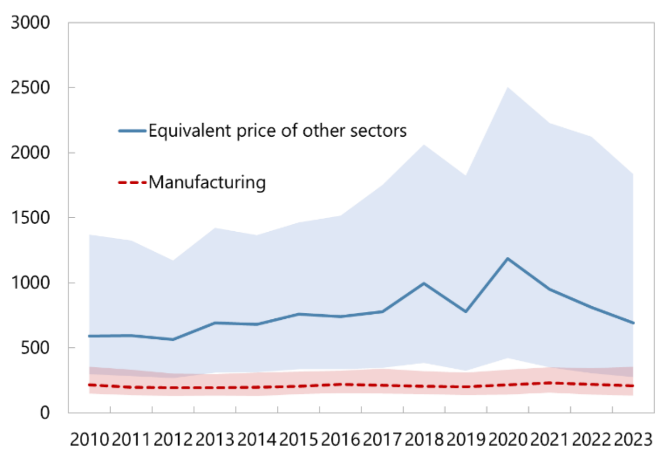
$$\hat{p}_{i,t} = \frac{\sum_{j \in S_{-m}} p_{j,t}}{N_{i,t}} ,$$

where p is the price in real RMB per square meter (deflated with the GDP deflator), S_{-m} is the set of all land transactions within a 1 kilometer radius of i and in non-manufacturing sectors, and N is the number of elements in S_{-m}.

The calculation of $\hat{p}_{i,t}$ uses the land registry data, which includes the universe of land sale transactions by governments (including local governments) in China—adding up to 1.6 million transactions in all sectors between 2010-23.[6] Observations with unit prices at the top and bottom percentiles, as well as those with less than two nearby non-manufacturing transactions ($N < 2$) are dropped to reduce the influence of outliers. After applying these filters, about 130,000 manufacturing observations remain, approximately a third of the total transactions in manufacturing, for which equivalent prices are computed.

Figure 3. Unit Prices of Land by Sector

(Real RMB per square meter; median and interquartile range)



Sources: Baidu Maps, Ministry of Natural Resources, Wind, and Staff calculations.

Note: Using a sample of 1.6 million land transactions, after excluding land for public uses, transactions with prices at the top and bottom percentiles, and transactions with less than two non-manufacturing nearby properties. The dotted line plots the median price for land sales to manufacturing firms. The solid line plots the median price for non-manufacturing transactions within 1 km of distance of each manufacturing transaction and in the same year. Shaded areas show interquartile ranges.

[6] The data are compiled by the Real Estate Registration Center of the Ministry of Natural Resources (available here).

Figure 3 displays the median of manufacturing prices ($p_{i,t}$) and the equivalent price for nearby transactions of non-manufacturing sectors ($\hat{p}_{i,t}$), respectively, in each year. While the median price in manufacturing has been roughly stable and slightly above 200 RMB per square meter, the unit price in other sectors has been consistently above 600 RMB per square meter, implying a price discount of at least 2/3 for land sold to manufacturing firms. The manufacturing discount picked up during the property market boom that ended in 2021, and subsequently eased with the property market correction, suggesting that the government shielded manufacturing firms from the generalized rise in the value of land.

The price gap between land used for manufacturing and other sectors could partly reflect differences in the degree of development of the land (e.g., whether a land plot has access to roads, water, or electricity connectivity). To test for this possibility, a regression analysis estimates to what extent the price gap is related to the “land grade” rating assigned by the government to each plot, which reflects government investment in the land. Specifically, unit prices for each transaction are regressed on a manufacturing dummy, as well as the area of the land (in logs), year fixed effects, and a set of categorical variables interacting the city with the land grade signifying the degree of land development.[7] The results show that differences in land development are not the main reason for the manufacturing discount. Including land grade information in the regression accounts for less than 10 percent of the discount, lowering the manufacturing gap coefficient from 616 to 567 RMB per square meter.

The land registry is also merged with information on firm type from Orbis to analyze differences in the prices of industrial land between SOEs and POEs.[8] Average differences in unit prices between the two types of firms are not statistically significant, and the ranking between two groups fluctuates over the years. Therefore, the data do not provide evidence that SOEs are systematically favored through cheaper industrial land.

Total Size of IP

Finally, the four IP instruments above are added up as a share of GDP to approximate the fiscal cost of IP. This requires additional calculations, as well as some extrapolation for the instruments that are estimated with data on listed firms.

- For cash subsidies, the aggregate subsidy is computed by adding up the subsidies for all listed firms as a share of their combined value added, and assuming the same subsidy rate applies to all non-listed firms.
- For subsidized credit, the subsidy rate by year is obtained from a regression interacting the manufacturing dummy in Table 1 with year fixed effects, and multiplying the resulting coefficients by the aggerate interest bearing liabilities of the manufacturing sector divided by total value added in WIND. This subsidy rate is applied to all manufacturing firms, including non-listed firms.[9]

[7] The interaction with city fixed effects is necessary as land grade ratings are not always comparable across cities.

[8] SOEs are defined as firms where public authorities are listed as a “global ultimate owner” with at least 50 percent of ownership in Orbis, following Cerdeiro and Ruane (2022). The remainder of the firms in Orbis are classified as POEs.

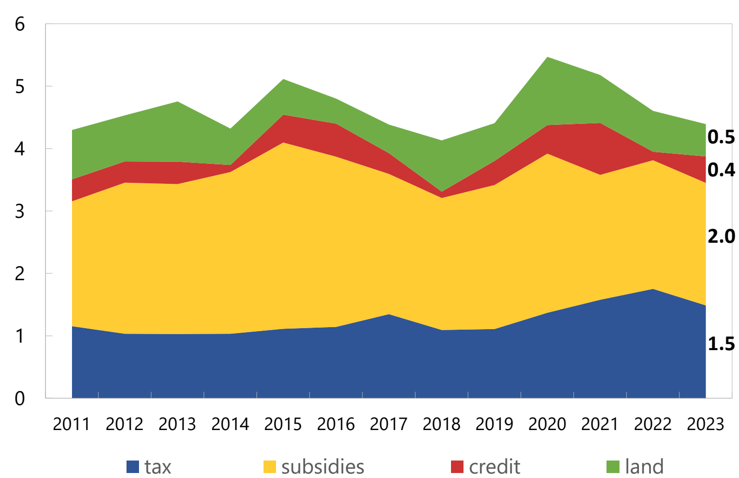
[9] A priori, it is not obvious whether cash and credit subsidy rates would be higher or lower for non-listed firms. Listed firms may have more administrative capacity and political connections to attract subsidies, but some subsidies are targeted to smaller firms. Annex II uses the structural model in Section 3 to provide an alternative estimate of the implicit fiscal cost of cash and credit subsidies that includes non-listed firms. While the analysis is not fully comparable, the results provide some tentative evidence that subsidies are somewhat smaller for non-listed firms. In particular, the structural model suggests cash and credit subsidies amounted to 1.5 percent of GDP in 2018, compared to the 2.2 percent of GDP estimated here using listed firm data. Therefore, the extrapolation here might be interpreted as an upper bound. For illustration, under the extreme assumption that non-listed firms did not receive any support at all, total IP would amount to about 1 percent of GDP.

- For tax benefits, the tax benefit rate computed from WIND is extrapolated to non-listed firms, correcting for the disproportionate share of corporate income taxes contributed by listed firms relative to their value-added share in the economy.
- For land subsidies, the aggregation assumes that the shadow market price of manufacturing properties is given by the price of nearby non-manufacturing properties $(\hat{p}_{i,t})$. Thus, the aggregate land subsidy rate is calculated as the discount rate for manufacturing $\left(\frac{\hat{p}_{i,t}-p_{i,t}}{p_{i,t}}\right)$ evaluated at median prices times aggregate land sales in the manufacturing sector as a share of GDP (equal to 0.3 percent in 2023).[10]

Combining the four instruments, Figure 4 shows that, in total, IP support has been equivalent to a subsidy of up to 4.4 percent of GDP as of 2023. The largest instrument are cash subsidies (2.0 percent of GDP in 2023), followed by tax benefits (1.5), land subsidies (0.5), and subsidized credit (0.4). The total size of IP in China has been broadly stable over time, although the composition by instrument has somewhat changed. Tax subsidies have grown in importance in the aftermath of the pandemic, as the government has progressively introduced more tax relief measures for firms, while use of other instruments has slightly diminished.

For comparison, state aid provided by EU countries—comprising cash subsidies, tax benefits, and credit subsidies—amounted to about 1.5 percent of GDP in 2022, with large manufacturing economies slightly above the average. Criscuolo et al. (2023) calculate a similar amount on average across 9 OECD economies. Hence, IP appears to be used more intensively in China.

Figure 4. IP Support by Instrument over Time
(percent of GDP)



Sources: Baidu Maps, Ministry of Natural Resources, Wind, and Staff calculations.
Note: Results for listed firms are extrapolated to all firms, correcting for the disproportionate share of CIT revenue contributed by listed firms. Financial firms are excluded. Labor costs (to calculate value added) are inferred from employee counts. Land subsidies and subsidized credit are based on advantages for the manufacturing sector relative to other sectors, excluding the real estate sector. The numbers on the right indicate the GDP shares of each category in 2023.

[10] Note that the calculation of aggregate cash subsidies and tax benefit rates is done for all sectors, while the calculations of subsidized credit and land subsidies is restricted to the manufacturing sector.

A few caveats are in order, though. First, the extrapolation to non-listed firms is heroic, absent data on those firms. Second, the calculation above does not account for general equilibrium effects, such as higher cash subsidies leading to lower interest rates or higher tax revenues. These factors could imply that Figure 4 overstates total support. On the other hand, IP support is also implemented through other instruments that are not covered here, such as sector-specific tax benefit beyond the corporate income tax or subsidized equity funding through Government Guided Funds, which may imply that the values in Figure 4 are an underestimate.

3. Impact on Misallocation and Productivity

In addition to generating direct costs for the entities providing support, IP may also lead to increased factor misallocation in the economy, lowering aggregate productivity. This section develops a structural estimation framework to relate IP to factor misallocation, and then uses it to calculate the impact of IP on aggregate TFP.

Model

Factor misallocation is defined following the Hsieh and Klenow (2009) model. In this model, heterogenous firms are equipped with a Cobb-Douglas production function

$$y_i = a_i k_i^{\alpha_s} l_i^{1-\alpha_s},$$

where i indexes the firm, y is output, a firm-specific TFP, k capital, l labor, and α_s the sector-specific capital share.

Each firm produces a differentiated product and operates in monopolistic competition, facing a constant elasticity of substitution (CES) demand function with elasticity σ. This implies that the price p it can charge is decreasing in the quantity produced y:

$$p_i \propto y_i^{-\sigma}.$$

Firms choose capital and labor to maximize profits given by

$$\pi_i = (1+\omega_i)p_i y_i - w l_i - r k_i,$$

where w denotes wages, r the rental cost of capital, and ω_i a production subsidy, which is meant to capture firm-specific distortions or wedges.

The key statistic in the model is the firm's total factor productivity in revenues (TFPR), defined as revenues per unit of inputs:

$$TFPR_i = \frac{p_i y_i}{k_i^{\alpha_s} l_i^{1-\alpha_s}}.$$

In equilibrium, profit maximization implies that TFPR only depends on firm-specific distortions:

$$TFPR_i \propto \frac{1}{1+\omega_i}\ .$$

The interpretation of this result is that, absent distortions, factors would reallocate across firms to chase any excess returns per unit of inputs, and so any TFPR differences would be traded away. Note that TFPR does not depend on TFP or physical productivity a, as in equilibrium a firm with higher TFP would expand production and lower prices until TFPR was equalized. Hence, differences in TFPR across firms can be used to infer the size of distortions and give a measure of factor misallocation.

Empirically, the usefulness of this approach is that the variables required to estimate TFPR are typically available in firm financial databases. In practice, empirical variation in TFPR might reflect multiple factors, including mismeasurement or adjustment costs, but it can also be driven by policies, and in particular IP. For example, firms receiving more subsidies will tend to produce above the subsidy-free optimum, i.e., employing too many inputs per unit of revenue, which will result in a lower TFPR. On the contrary, firms with more market power, for example those protected by barriers to competition or growth, will tend to produce below the optimal level in order to charge higher prices, resulting in a higher TFPR.[11]

Another useful equilibrium result of the model is that aggregate TFP can be approximated as an additive function of the variance in TFPR:[12]

$$\log TFP \cong \frac{1}{\sigma-1}\log\left(\sum a_i^{\sigma-1}\right) - \frac{\sigma}{2}\operatorname{var}\left(\log TFPR_i\right). \quad (1)$$

This will allow to calculate the aggregate TFP impact of IP through its effects on a and TFPR.

Empirical Approach

Next, the following empirical hypotheses guided by the model are formulated:

- *Hypothesis 1:* Sectors with higher subsidies tend to feature lower sector-level TFPR.
- *Hypothesis 2:* Sectors subject to entry barriers from trade or regulatory policies tend to feature higher sector-level TFPR.
- *Hypothesis 3:* In general, sectors with more IP measures tend to have higher TFPR dispersion *within* the sector.
- *Hypothesis 4:* IP does not affect firm-level TFP.

Hypotheses 1 and 2 are directly related to the equilibrium result for TFPR. Hypothesis 3 is based on the presumption that IP may not apply to (or benefit) all firms equally, even for a given level of IP intensity in a sector. Hypothesis 4 is just an assumption in the model.

To test these hypotheses, the following regression specification is used:

$$y_{2018,s} = \boldsymbol{\beta_x} * \boldsymbol{IP^x_{2009-18,s}} + \delta * y_{2008,s} + \gamma_{\bar{s}} + \epsilon_s \quad (2),$$

where s indexes the sector at NACE 4-digit level, y is the dependent variable relevant to each hypothesis, $\boldsymbol{IP^x_{2009-18,s}}$ is a vector with the cumulative intensity of IP measures in sector s over the 2009-18 period for different IP instruments indexed by x (e.g., cash subsidies, tax benefits, etc.), $\gamma_{\bar{s}}$ is a sector fixed effect for a less granular level of sectoral aggregation than s (NACE 2-digit), which controls for broader demand or technological factors, and ϵ_s is an independent error term, potentially correlated within each broad sector $\bar{s}$. Note that the specification controls for the level of the dependent variable in the year prior to the period of

[11] It can be shown that a lower elasticity of substitution σ, a common proxy for higher market power, would be reflected as a lower measured TFPR

[12] The approximation is exact if a and $TFPR$ are jointly log-normally distributed.

analysis, and captures the impact of IP over a decade. This allows for time lags in the effective implementation of IP, as well as in the reallocation of production factors in response to IP.[13]

IP intensity is defined as:

$$IP^{x}_{2009-18,s} = \log\left(1 + \sum_{t=2009}^{2018} NIP^{x}_{t,s}\right),$$

where NIP is the number of IP measures of type x covering a given sector in a given year, and the 1 between the parentheses permits to include sectors with zero IP measures during the period of analysis.

The dependent variable y depends on the hypothesis tested. For Hypotheses 1 and 2, it is the sector-level average of $log(TFPR_{i,t})$; for Hypothesis 3, the interquartile range of $log(TFPR_{i,t})$ within each sector (which is more robust to outliers than other measures of dispersion); and for Hypothesis 4, the sector-level average of $log(TFP_{i,t})$. The time range 2009-18 is given by data availability constraints, as the IP counts data starts in 2009, whereas the sample size for China in Orbis diminishes severely after 2018.

While the introduction of IP measures can be driven by myriad factors and cannot be treated as an exogenous variable, IP intensity is not found to be statistically related with the initial (year 2008) values of any of the dependent variables used. Still, the results presented in this section should be interpreted as associations rather than causal estimates.

Data

The estimation of regression specification (2) requires merging sector-level data on IP counts with firm-level data on TFPR and TFP. The IP counts data were kindly shared by the authors of Juhasz et al. (2025), which use a text-based analysis to identify IPs in the GTA database. Admittedly, the GTA is an imperfect measure of IP intensity, for various reasons. First, it only captures the number of policies irrespective of their size. Second, it only considers nationwide, not subnational, policies.[14] Yet, it is the only measure publicly available at the economy level and covering an extended period and wide set of IP instruments.[15]

Figure 5.1 shows the ranking of economic sectors by the number of IP measures in effect.[16] Similar to the direct method results in Figure 1, manufacturing sectors (blue bars), and particularly high-tech manufacturing sectors, tend to be at the top. Figure 5.2 ranks IP measures by their average prevalence (defined as the share of goods covered), using the classification of measures in the GTA database. The most frequent IP measure is tax relief, although this may reflect the fact that tax benefits tend to cover more sectors than more targeted forms of IP, while trade policy measures and subsides are also common. In what follows, IP measures are reclassified into five broader categories that are better aligned with the structural framework: subsidized credit,

[13] The limited time period available in the data, coupled with potentially long lags in the effects of IP, make a panel specification unviable.

[14] While subnational measures are highly prevalent in China, their sectoral distribution is found to be strongly correlated with nationwide directives (Fang et al., 2025).

[15] The analysis in Section 2 covers a narrower set of instruments and, for most instruments, is based on data from listed firms only.

[16] This requires mapping HS2012 6-digit goods (available in the GTA database) to NACE 4-digit sectors. The mapping code is available upon request.

other subsidies, tax relief, trade barriers, and regulatory barriers (see Annex I for the classification details). These five categories are used as the regressors ($IP^{x}_{2009-18,s}$) in equation (2).

The estimation of firm-level TFPR combines firm-level data from Orbis and sector-level data from KLEMS. Empirically, TFPR is calculated as:

$$\widehat{TFPR}_i = \frac{value\ added_i}{(fixed\ assets_i)^{\alpha_{s,t}}(labor_i)^{1-\alpha_{s,t}}}.$$

Value added is defined as gross output minus intermediate inputs. For firms without data on the cost of employees (most of the sample), labor input is proxied by the firm's cost of goods sold (from Orbis) times the sector-level share of labor costs in the cost of goods sold (from KLEMS), following Cerdeiro and Ruane (2022), while intermediate inputs are the remainder of cost of goods sold. The capital share $\alpha_{s,t}$ is estimated with the average capital to value added across countries expected to feature less distortions—the countries at the bottom quarter by cross-sectoral TFPR dispersion in KLEMS (in ascending order: Sweden, Denmark, Czechia, Japan, and Italy).[17] NACE 4-digit sector with less than 10 observations in a given year are excluded. When testing hypotheses 1 and 2, the firm-level TFPR is averaged at the sector level. When testing hypothesis 3, the interquartile range within the sector of the estimated firm-level TFPR is used.

For testing hypothesis 4, firm-level TFP is obtained from Diez et al. (2021), which apply the Ackerberg et al. (2015) estimation procedure to Orbis data.

Figure 5.1. Intensity of IP by sector, 2009-22
(Number of measures in effect, average per year)

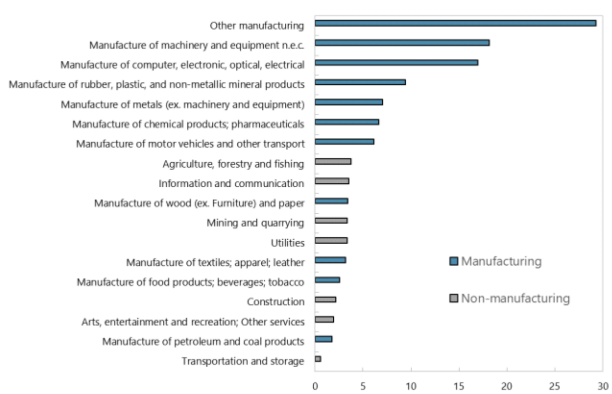
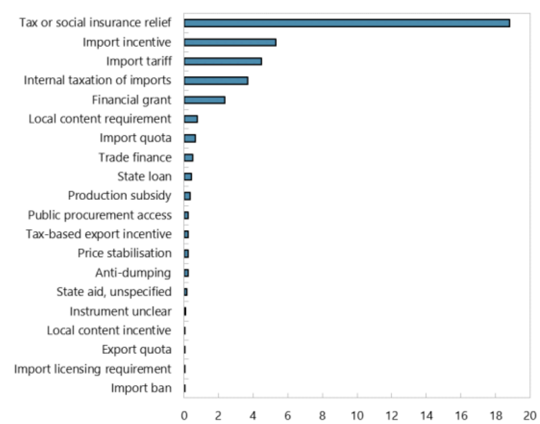


Figure 5.2. Intensity of IP by measure type, 2009-22
(Percent of goods affected, average per year)



Sources: GTA database, Juhasz et al. (2025), KLEMS, Orbis, and IMF Staff calculations.
Notes: sectors are defined as NACE letter categories, and goods as HS2012 6-digit categories.

Results

Between-sector misallocation

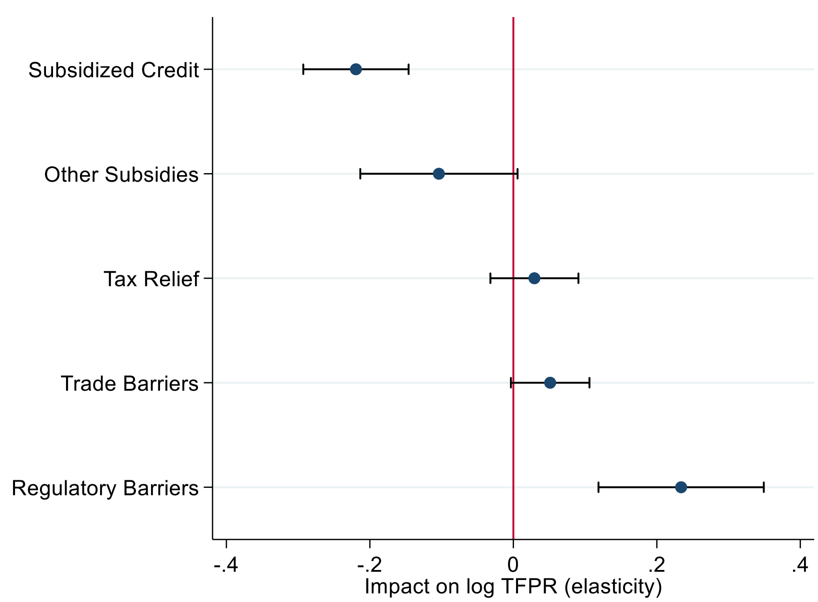
[17] In Hsieh and Klenow (2009) the benchmark is the US.

Hypotheses 1 and 2 are tested first, using specification (2) with the 5 types of IP measures included simultaneously as separate regressors. Figure 6 displays the estimated elasticity of sector-level TFPR to increases in the intensity of each IP measure type. The results support the hypotheses: subsidies, either in the form of credit or cash, tend to lower a sector's TFPR, while trade and regulatory barriers tend to increase it. The coefficient for subsidized credit is larger in absolute terms and more statistically significant than the one for other subsidies. Yet, other subsidies are twice as frequent in the data, so their total impact on TFPR outcomes is larger, consistent with the results in Section 2.

The result for taxes is ambiguous and statistically insignificant, however. A potential interpretation is that some tax credits encourage production, like subsidies, but others are only given to small firms and thus discourage growth in inputs, which would be reflected as a higher TFPR. It is also possible that the effect of taxes is statistically harder to identify, as tax measures tend to be less targeted to a few sectors (Figure 5.2).

The regression measures the impact of average IP intensity between 2009 and 2018 on TFPR outcomes in 2018, but broadly similar results are obtained if the dependent variable is defined as the average outcome over 2015-18. The results are also robust to using the median log(TFPR) by sector as the dependent variable instead of the average.

Figure 6. Impact of IP on Sector TFPR by Measure, 2009-18



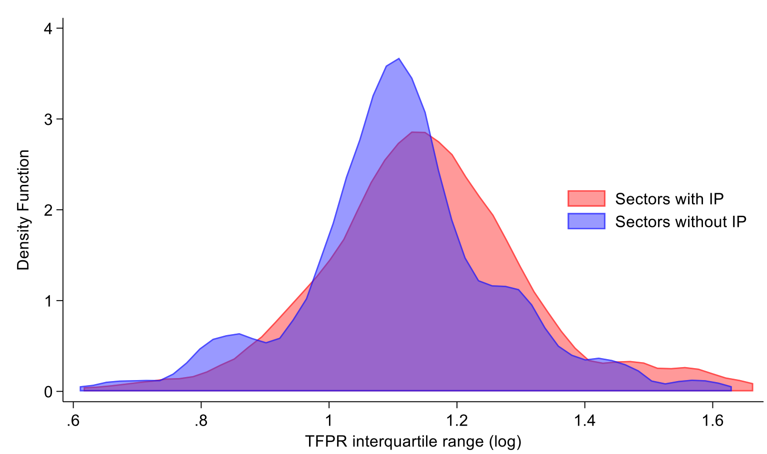
Sources: GTA database, Juhasz et al. (2025), KLEMS, Orbis, and IMF Staff calculations.
Notes: Based on a sector-level regression at NACE 4-digit level, with NACE 2-digit sector fixed effects, using 2018 firm-level data for China and IPs over 2009-18. The regression excludes the agriculture, finance, and non-market sectors, as well as NACE 4-digit sectors with less than 10 observations in a given year. Whiskers indicate 90-percent confidence intervals, with standard errors clustered at the NACE 2-digit sector level.

Within-sector misallocation

Next, the impact of IP on within-sector TFPR dispersion is analyzed (Hypothesis 3). Figure 7 shows that in sectors subject to at least some IP between 2009 and 2018 (red curve), the distribution of the interquartile range of log(TFPR) within the sector is shifted to the right relative to sectors with no IP measures, suggesting that IP is associated with greater within-sector misallocation. While the measure of IP only varies at the sector level, it appears that the distortions IP generates are heterogenous across firms within a sector, either because not all firms have equal access to IP benefits or because they are unevenly affected by them (e.g., export-oriented firms would be more affected by export incentives).

This difference is also tested formally by using specification (2) with the within-sector interquartile range of log(TFPR) used as the dependent variable and a dummy variable indicating whether the sector was subject to IP measures as the main independent variable. The coefficient on the dummy indicates that sectors with some IP have 14 percent higher within-sector TFPR dispersion, and the difference is statistically significant. Similar results are obtained using IP intensity as the regressor instead of a dummy, or alternatively using the standard deviation of TFPR as a dependent variable instead of the interquartile range. The result is also in line with Chen et al. (2022), which estimates a 6 percent increase in the within-sector variance of log(TFPR) for industries targeted by IP in the 10th 5-Year Plan (2001-05).

Figure 7. Impact of IP on within-Sector TFPR Dispersion, 2009-18



Sources: GTA database, Juhasz et al. (2025), KLEMS, Orbis, and IMF Staff calculations.
Notes: Based on a sector-level regression at NACE 4-digit level, with NACE 2-digit sector fixed effects, using 2018 firm-level data for China and industrial policies over 2009-18.

Contribution to misallocation and cross-country comparison

Taken at face value, the regression results presented above suggest that IP measures tend to generate factor misallocation between and within sectors. At the same time, IP intensity may be correlated with pre-existing TFPR distortions, and some IP measures may offset the effects of others at the sector level (since various IP measures shift TFPR in opposite directions as illustrated in Figure 6).

To systematically calculate the contribution of IP to between-sector misallocation, Figure 8.1 shows the share of the dispersion in log(TFPR) explained by IP in the regression. Specifically, the full bar plots the standard deviation of log(TFPR) residuals in specification (2), but excluding the five IP instruments ($\boldsymbol{IP^{x}_{2009-18,s}}$) and the initial TFPR level from the regressors, and weighing the standard deviation by sector value added. And the red bar plots the difference between the full bar and the same statistic but including the five IP instruments as regressors. Thus, the red bar reflects the contribution of IP to overall between-sector TFPR dispersion, which is estimated at 24 percent.[18]

Similarly, Figure 8.2 shows the contribution of IP to total within-sector misallocation. In this case, the full bar shows the average within-sector TFPR standard deviation,[19] while the red bar plots the predicted values from Hypothesis 3, both weighed by the value added of each sector:

$$\sum_{s} \widehat{\beta_{all}} * IP^{all}_{2009-18,s} * value\ added_{2018,s}.$$

IP only explains 4 percent of total within sector misallocation, a considerably smaller share than for between-sector misallocation. This is probably because the main goal of IP is to transform the sectoral structure of the economy, and within-sector distortions may be more of an unintended by-product. Moreover, overall misallocation between firms is three times as large as between sectors, so while IP explains a smaller share of the total within-sector misallocation, this can have significant effects on aggregate productivity.

Figure 8.1. Between-Sector TFPR Dispersion, 2018
(log TFPR, standard deviation)

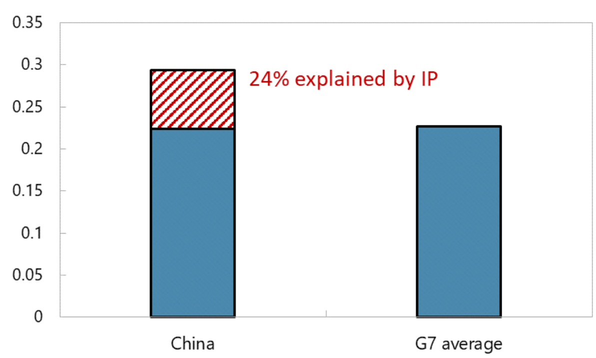
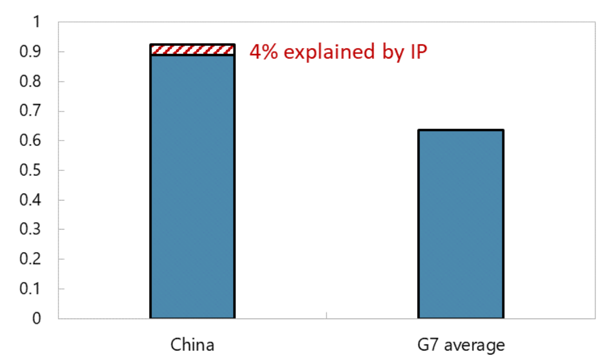


Figure 8.2. Within-Sector TFPR Dispersion, 2018
(log TFPR, standard deviation)



Sources: GTA database, Juhasz et al. (2025), KLEMS, Orbis, and IMF Staff calculations.
Notes: the G7 average includes countries with sufficiently large samples in Orbis: DE, FR, GB, IT, JP. The shares explained by IP are based on the regressions in specification (2).

To provide an international benchmark, these calculations are replicated for G7 countries with sufficiently large samples in Orbis: France, Germany, Italy, Japan, and the United Kingdom. Notably, in the G7 countries the relationship between IP and misallocation (Hypotheses 1-3) is not statistically significant, neither between nor within sectors. This is probably because IP was much less relevant and/or less distortive in those countries, at least during the 2009-18 period—prior to the recent wave of IPs in advanced economies. The result is consistent with Machado Parente et al. (2025), which find no medium-term effects of IP on within-sector

[18] Figure 8.1 is expressed in terms of the standard deviation for ease of interpretation and comparability with Figure 8.2.
[19] Log(TFPR) is assumed to be normally distributed to calculate the standard deviation from the interquartile range (used as the dependent variable in Hypothesis 3).

allocative efficiency for a large sample of countries. Hence, the G7 bars in Figures 8.1 and 8.2 only display overall misallocation. As expected, G7 countries tend to have less overall misallocation than China, and part of that gap may be explained by IP-induced misallocation in China, especially for between-sector misallocation.

Firm-level TFP

Specification (2) is also used to test the relationship between IP and average firm-level TFP of a sector (Hypothesis 4). In this case, no statistically significant results are obtained under any specification. The same holds true if the dependent variable is the sector-level average (or median) *change* in within-firm log(TFP) between 2008 and 2018, instead of the sector-level average log(TFP) in 2018 (controlling for the 2008 level) as in specification (2). This is consistent with the results in Chen et al. (2022) and Fang et al. (2025), while Branstetter et al. (2023) find a negative effect of IP on firm-level TFP. In principle, some IP measures such as sector-specific innovation incentives might be expected to raise firm-level TFP over time, but that may be offset by other IP measures that create barriers to competition or reward laggard firms, thus discouraging innovation. Measurement error in the estimation of TFP, which relies on stronger assumptions than TFPR, might also attenuate the results. Given the null result, the calculation of the impact of IP on aggregate TFP can abstract from impacts through firm-level TFP and focus on the misallocation channel only.

Aggregate TFP Impact

The regression results can be used in combination with the model to calculate the aggregate TFP loss from greater misallocation. This involves comparing the variance of log(TFPR) residuals with and without controlling for IP measures, and plugging the difference in equation (1), assuming $\sigma = 4$ as in Hsieh and Klenow (2009). IP-induced misallocation is found to lower aggregate TFP in China by 1.2 percent, with 1.0 percentage points of that coming from misallocation between sectors, and the remaining 0.2 from within sectors. Assuming capital adjusts endogenously, this could imply a GDP level loss of up to 2 percent. However, these results may be interpreted as a lower bound, as potential mismeasurement of IP intensity could generate attenuation bias in the estimates.

Annex II uses the model to infer the implicit fiscal cost of IP subsidies (including cash and credit), providing a cross-check for the results in Section 2.

Industrial Champions

As a final step, the analysis examines the role of industrial champions, or market leaders (defined as the firm with the largest revenue share in each sector), which have also been viewed as benefiting from IP in many countries. The firm-level data on TFP and TFPR are used to shed light on the drivers of their commercial success—whether it is driven by real productivity (higher firm-level TFP), barriers to competition (which would result in higher firm-level TFPR), or policies encouraging production (lower firm-level TFPR).

Figure 9.1 shows that in most sectors, leading firms have higher TFP than the average firm. This is expected, as it would be the outcome of the model under no distortions. However, Figure 9.2 shows that leaders typically have lower TFPR than the average, implying that they are producing at inefficiently high levels. This is particularly true for SOE leaders, consistent with the findings in Jurzyk and Ruane (2021).[20] Therefore, it seems that in most sectors, market leaders do not owe their position to barriers to competition, but to both higher

[20] As in Section 2, SOEs are defined as firms where public authorities are the majority "global ultimate owner" in Orbis.

productivity and policies encouraging production. The latter may include subsidies of different kinds and, in the case of SOEs, and especially central SOEs, implicit credit guarantees by the government.

Figure 9.1. TFP of Sector Leader Relative to Sector Average, 2018

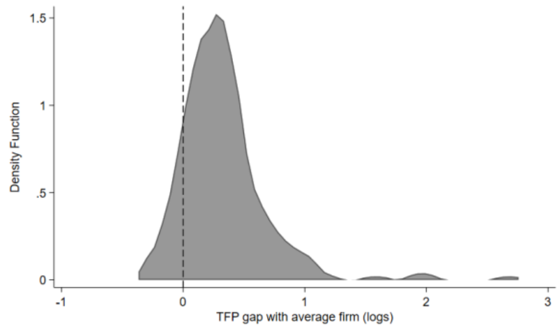
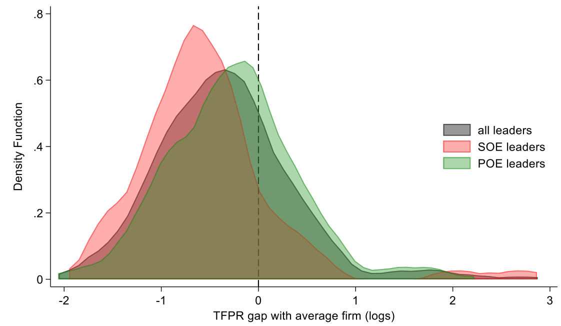


Figure 9.2. TFPR of Sector Leader Relative to Sector Average, 2018



Sources: KLEMS, Orbis, and IMF Staff calculations.
Notes: the charts show the distribution of gaps between the sector leader and the average firm across NACE 4-digit sectors.

4. Conclusion

This paper quantifies the equivalent fiscal cost of IP in China at about 4 percent of GDP per year, based on an instrument-by-instrument estimation using data from listed firms and the land registry. Moreover, using a structural model, it estimates that misallocation from IP reduces aggregate productivity by about 1.2 percent, and GDP by up to 2 percent.

These results resonate with Fund policy recommendations on IP in China (IMF 2024a). First, the authorities should increase transparency around IP, both to improve policymaking as well as to allay concerns of trading partners. This would require enhancing information collection, particularly on local government IP measures. While this paper aims to approximate the magnitude and modalities of Chinese IP, the authorities are best placed to conduct a comprehensive assessment. Second, scaling down IP would reduce factor misallocation and fiscal costs, which are sizeable according to the paper's estimation. IP should be pursued cautiously and only to tackle well-defined market failures (IMF 2024b). And third, to the extent that IP is implemented, it should take the form of budgetary tools, which tend to be more transparent and less distortionary than more indirect measures like credit allocations or regulation (IMF 2024c). As shown in Figure 4, China has already made some progress in that direction.

The calculations in the paper are subject to some caveats. The analysis aims to cover as many IP instruments as the data allow. However, further research is needed to quantify other instruments, such as Government Guided Funds or Public-Private Partnerships, which may also be redirecting capital to priority sectors. Moreover, the paper makes strong assumptions to overcome data gaps, such as extrapolating results to non-listed firms for some IP instruments, or relying on IP counts data for the structural estimation. Progress on data reporting would facilitate a more accurate characterization of the size of Chinese IP and its economic effects.

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Annex I. Data

Listed Firm Financials

Data on listed firm financials is obtained from WIND and covers all A-listed firms in Mainland China, including firms listed in the Beijing, Shanghai, and/or Shenzhen stock exchanges. WIND is the reference database for financial information on listed firms in China.

The following definitions are used to construct variables:

- *Value added* is constructed as revenues minus operating costs net of labor costs, where labor costs are approximated as the firm's labor count times urban wages from the NBS, and rescaled to match the aggregate labor share in KLEMS.
- *Interest expenses* are defined as interest expense minus income (TTM) prior to 2018, as gross interest expenses are unavailable for those years.
- *Long-term debt* is defined as long-term loans plus bonds payable. The short-term debt share equals one minus long-term debt over total interest-bearing debt.

Tables A.1 lists the summary statistics for the main variables used in the analysis. Table A.2 displays the number of firms with available information in each year and their aggregate value added as a share of economy-wide GDP, which amounts to about 9 percent in 2023.

Table A.1. Summary Statistics of Main Variables

Variable	Unit	Mean	first quartile	median	third quartile	Number of obs.
total revenue	Billion RMB	8.51	0.46	1.16	3.42	59,270
total assets	Billion RMB	12.90	0.82	2.14	5.99	59,268
value added	Billion RMB	1.44	0.16	0.36	0.91	56,999
subsidy ratio	percent	6.2	1.0	2.2	4.4	52,222
income tax rate	percent	15.0	10.2	14.3	20.0	58,345
effective interest rate	percent	-142.5	3.0	4.6	6.5	43,537
manufacturing dummy	-	0.70	0	1	1	70,416
debt/assets	percent	14.9	1.4	10.9	24.2	59,282
short-term debt/ total debt	percent	76.6	57.6	92.2	100.0	50,023
intangible assets / total assets	percent	4.8	1.6	3.3	5.8	57,803
return on assets	percent	6.5	2.4	5.5	9.7	53,807
indsutry price-to-earnings ratio	ratio	96.2	12.9	51.1	123.1	65,292

Source: WIND.

Table A.2. Sample size by year

Year	Number of obs.	Percent of GDP
2010	2,418	4.8
2011	2,948	5.2
2012	3,368	5.0
2013	3,830	5.2
2014	4,082	5.3
2015	4,082	5.3
2016	4,388	6.0
2017	4,703	6.9
2018	4,831	7.6
2019	4,930	7.7
2020	4,931	8.0
2021	4,962	8.7
2022	4,915	9.1
2023	4,882	8.8

Source: WIND.

Note: the sample only includes firm-year observations with non-missing revenue and non-negative value added. The rightmost column shows total value added in the sample as a percent of GDP.

Land Registry

The land registration data is sourced from the China Land Market website (www.landchina.com), which is hosted by the Real Estate Registration Center of the Ministry of Natural Resources and guided by the Department of Natural Resource Development and Utilization of the Ministry of Natural Resources. The time period spans from 2010 to 2023, following the Chinese government's 2007 mandate for land transaction transparency and public disclosure. The dataset consists of individual land registration records, covering land uses such as general commercial residential, industrial, and commercial land, and excluding public land. Specifically, the selected land use categories include Accommodation and Catering Land, Business and Financial Land, Catering Land, High-End Residential Land, Hotel Land, Industrial Land, Medium-Low Price, Medium-Small Unit Ordinary Commodity Housing Land, Other Commercial and Service Land, Other Ordinary Commodity Housing Land, Research and Development Land, Retail Commercial Land, Storage Land, Urban Residential - Ordinary Commodity Housing Land, and Wholesale and Retail Land.

Each land registration record includes a description of its specific geographic location. Based on this, the latitude and longitude coordinates were retrieved via Baidu Maps, and the distance to the city and county center was calculated using the central coordinates provided by Baidu Maps. Additionally, the land registration records specify the industry in which the land is to be used. Industry classification follows China's Classification of National Economy Industries (GB/T 4754–2017), which allows for direct identification of whether a given subsector belongs to the manufacturing industry.

After excluding missing values and failed matches, the final dataset comprises about 1.6 million land transaction records. Table A.3 shows the number of transactions per year.

Table A.3. Sample size by year

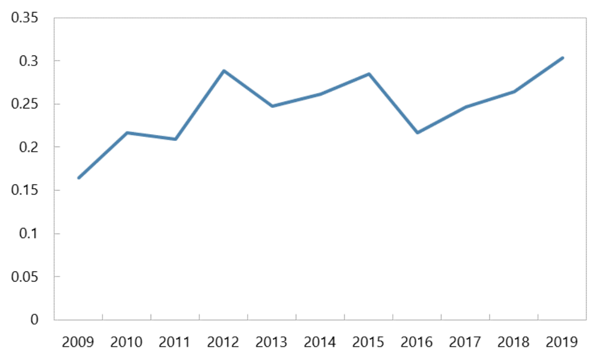
Year	Number of obs.
2010	136,055
2011	149,955
2012	135,017
2013	163,763
2014	128,665
2015	105,898
2016	96,581
2017	102,591
2018	129,089
2019	78,749
2020	103,458
2021	121,896
2022	105,312
2023	84,227

Source: Ministry of Natural Resources and Staff calculations.
Note: number of firms with non-missing revenue and non-negative value added.

IP Counts

A detailed description of the dataset is available in Juhasz et al. (2025).[21] Figure A.1 shows the average number of IP counts per sector over time, which displays a slight upwards trend (in contrast with Figure 4, which shows a broadly stable size of IP).

Figure A.1. IP counts per sector.



Source: Juhasz et al. (2025).
Note: the chart displays the average number of IP measures in effect in each year per NACE 4-digit sector.

Table A.4 shows how the types of IP measures available in the GTA database are collected into 5 broader categories for the analysis in Section 3.

[21] The authors of Juhasz et al. (2025) shared these data on September 2024.

Table A.4. Classification of IP Measures.

Trade barriers	Tax relief	Regulation	Subsidized financing	Other subsidies
Import ban	**Import incentive**	**Public procurement access**	**State loan**	**State aid, unspecified**
Export quota	**Tax or social insurance relief**	Intellectual property protection	**Trade finance**	**Financial grant**
Internal taxation of imports	**Tax-based export incentive**	Labour market access	Interest payment subsidy	**Production subsidy**
Import tariff	Other export incentive	Post-migration treatment	Capital injection and equity stakes	**Price stabilisation**
Anti-dumping		Public procurement localisation	Loan guarantee	In-kind grant
Local content requirement		Public procurement preference margin	Financial assistance in foreign market	Price stabilisation
Import quota		Public procurement, nes	Trade payment measure	State aid, nes
Local content incentive				Export subsidy
Import licensing requirement				FDI: Financial incentive
Export ban				
Export licensing requirement				
FDI: Entry and ownership rule				
FDI: Treatment and operations, nes				
Import tariff quota				
Import-related non-tariff measure, nes				
Local operations incentive				
Local value added incentive				

Source: GTA database and Juhasz et al. (2025).

Note: measures highlighted in red are those China uses and are captured by the Juhasz et al. (2022) definition of IP. The list of measures within each broad category is based on the GTA classification.

Non-listed Firm Financials

The data on firm financials are from the Bureau Van Dijk's Orbis database, retrieved as of November 2024, which has extensive coverage of Chinese firms from the early 2000s and up to 2018. These data are merged with data on IP counts (available for 2009-22) at the NACE 4-digit sector level.

Tables A.5 and A.6 list the summary statistics for the main variables used in the sector-level regressions, and the number of firms with available information in each year, respectively. Table A.6 shows that 2018 is the latest year with a large sample in Orbis.

Table A.5. Summary Statistics at the Sector Level, China, 2018

Variable	Mean	Std. deviation	Num of sectors
log TFPR	0.87	0.46	295
IQR of log TFPR	1.13	0.42	295
log TFP	1.29	0.69	295
IP dummy all	0.48	0.50	279
IP intensity all	0.77	0.95	279
IP intensity credit	0.03	0.19	279
IP intensity subsidy	0.10	0.24	279
IP intensity tax	0.47	0.74	279
IP intensity external	0.45	0.69	279
IP intensity regulatory	0.01	0.13	279

Sources: KLEMS, Juhasz et al. (2025), and Orbis.

Notes: statistics at the NACE 4-digit sector level, excluding sectors with less than 10 firms with TFPR values.

Table A.6. Sample size by year

Year	Num. of firms
2009	306,702
2010	263,309
2011	240,792
2012	231,326
2013	340,543
2014	287,507
2015	445,454
2016	444,343
2017	511,624
2018	455,798
2019	40,079
2020	27,705
2021	11,602
2022	5,071

Sources: KLEMS, Juhasz et al. (2025), and Orbis.

Notes: including firms with positive fixed assets.

Annex II. Implicit Fiscal Cost from Structural Estimation

The model presented in Section 3 can also be used to estimate the implicit fiscal cost of IP subsidies, since in equilibrium the model yields an analytical expression relating TFPR distortions and subsidies (ω):

$$\log TFPR \propto\approx -\omega\ .$$

This can be combined with the estimated impact of IP subsidies on sector-level log(TFPR) from regression specification (2), to obtain the fiscal cost as:

$$\sum_{s} -(\widehat{\beta_{cash}} * IP^{cash}_{2009-18,s} + \widehat{\beta_{credit}} * IP^{credit}_{2009-18,s}) * value\ added_{2018,s}.$$

Note the calculation above includes both cash and credit subsidies, but excludes tax benefits as their estimated coefficient is close to zero and has the opposite sign as the ones for subsidies (see Figure 6).

The estimated fiscal cost of subsidies under this method is 1.5 percent of value added in 2018, which is somewhat lower than the estimate for listed firms in Section 2 of 2.2 percent in the same year. This could reflect that listed firms are able to capture more subsidies, perhaps because they have larger administrative capacity or closer political connections, suggesting that the extrapolation of subsidy rates to non-listed firms in Section 3 may somewhat overstate the size of IP. However, the estimate here may be subject to attenuation bias, as it relies on an imperfect measure of IP (narrative IP counts), so the result remains tentative.

PUBLICATIONS

Industrial Policy in China: Quantification and Impact on Misallocation
Working Paper No. WP/2025/155