How Do Robot Subsidies Affect Aggregate Productivity and Firm Dispersion? Theory and Evidence from China

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Abstract

This study examines the effects of robot subsidies in China's manufacturing sector. Exploiting differences in the timing of the subsidy implementation across municipalities, I find the introduction of a robot subsidy has heterogeneous impacts across firms of different scale. Although the subsidy results in a 13 percent increase in applications for robot patents, the facilitated access to robotics leads to a 14 percent reduction in new firm's entry in the manufacturing sector, along with a significant increase in turnovers of bigger industrial enterprises. Using a stylised model, I show that the interaction between financial frictions and endogenous automation helps reconcile the empirical findings: ex-ante capital misallocation causes a uniform subsidy to disproportionately benefit firms with better access to capital. The distortion creates an efficiency trade-off: while a subsidy can enhance overall automation, it also exacerbates automation dispersion, which reduces efficiency. To quantify the net efficiency impact of these competing forces, I embed this mechanism into a dynamic heterogeneous firm model, calibrated to match key features of the Chinese industrial sector. The model indicates that a robot subsidy of 20% narrows the gap between mean and optimal automation levels by 22 percentage points, while raising automation dispersion by 49 percentage points. This leads to a 1.2 percent increase in aggregate output, along with a 2.4 percent decline in total factor productivity.

Keywords: Industry Policy, Robot and Automation, Financial Frictions

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1 Introduction

The adoption of robotic technology is part of a live and lively debate across the world, with many countries concerned about its impact in terms of displacing labour and exacerbating inequality. In recent years, China has firmly established itself as a leader in robot integration. As indicated in *Made in China 2025*, a national strategy to boost manufacturing published in 2015, China aims to become the world leader in the robotics industry.[1] The *14th Five-Year Plan for Robotics Industry Development*, published in 2021, specifies China's ambition of boosting robot density to 500 units per 10,000 workers by 2025.[2] Under those policy initiatives, there was a sharp increase in China's use of robots. By 2021, China's robot density had soared to 322 per 10,000 workers, not only overtaking the United States, at 274, but also positioning China fifth in the world, after South Korea, Singapore, Japan and Germany.[3] In 2022, the country's sales of industrial robots amounted to 290,300 units, representing approximately 52 percent of global industrial robot shipments. Cheng et al. (2019) provides comprehensive details of China's advancement in industrial robot adoption.

While there are multiple reasons behind the rapid growth of industrial robot utilization in China, strong government support is amongst the most important. The impact of China's robot-supporting policy, however, has not yet been thoroughly studied in the literature. The goal of this paper is to evaluate the impact of robot subsidies on the manufacturing industry in China. First, exploiting data on robotics industry activities, I empirically investigate the impacts of robot subsidies and document that subsidies lead to a significant increase in robotics industry activities; reduce firm entry into the manufacturing sector; and disproportionately benefit larger firms, with them seeing significant increase in turnover, total asset and employment. Second, I propose a simple model to illustrate how the interaction between

[1] The Made in China 2025 initiative is a strategic plan launched by the Chinese government in 2015 to upgrade the country's manufacturing sector and move from low-cost mass production to more high-tech industries. The plan focuses on key sectors such as robotics, clean energy, and advanced information technology.

[2] The 14th Five-Year Plan for Robotics Industry Development is a strategic initiative launched by the Chinese government in 2021 to boost technological advancement in the robotics sector. The plan focuses on enhancing core technologies, expanding applications in industries such as manufacturing, and improving China's global competitiveness in robotics.

[3] In 2022, the average robot density in China was 392, while in the United States, Germany, Japan and the world it was 285, 415, 397 and 151, respectively.

financial frictions and endogenous automation could explain the empirical findings, as well as to elucidate the main efficiency trade-offs stemming from a uniform robot subsidy. Finally, I embed the mechanisms in the simple model into a dynamic framework with heterogeneous households and use the framework to gauge the efficiency trade-offs; specifically, the richer model allows me to quantify the dynamic capital misallocation losses resulting from the higher dispersion in firms' automation levels caused by the subsidy and weigh them against the efficiency gains from higher robot adoption.

To carry out the first step of the paper, I use the Peking University (PKU) Law dataset and apply a text recognition approach (Juhász et al., 2022) to identify a subsidy as a demand-side robot subsidy. The text criteria required for a demand-side robot subsidy are: (1) the incorporation of keywords linked to robotics; (2) the inclusion of a comprehensive subsidy plan; (3) the specification of subsidy-specific terminology. I successfully identify 244 municipal-level industrial robot demand-side subsidy policies, which are characterized by three key features: (a) non-exclusiveness, in the sense of uniform accessibility and intensity across robot buyers, (b) local preferences, with exclusive or progressive supports provided to locally produced robots, and (c) strong support, captured by significant financial supports.

To empirically assess the impact of the subsidy, I exploit differences in the timing of the subsidy implementation across municipalities. The key identification assumption is that the timing of subsidy introduction is uncorrelated with my outcomes of interest. The assumption is supported by the descriptive evidence that the pre-treatment trends of outcomes between early and late adopters are parallel. Technically, I employ difference-in-differences with synthetic weights (SDID) approach (Arkhangelsky et al., 2021) as my main identification strategy. This approach constructs a counterfactual group, which resembles the socioeconomic conditions of municipalities before the implementation of the subsidy policy. The after-treatment difference between the treated municipalities and the synthetic control group then provides an estimate of the subsidy's causal impact.

I obtain two facts from the empirical study. First, I find that the subsidy policy is effective in promoting robot utilization. Although direct municipal-level measures of robot utilization are unavailable, the local preference characteristic suggests that the increased demand for robots largely remains within the local supply chain. Consequently, I evaluate the impact of robot subsidies from two supply-side perspectives - robotics-related innovation and new robotics firms entry. In terms of the total number of applications for robotics patents, I find a 13.6 percent increase in applications after the introduction of the policy. In terms of the number of robotics firms, I find a 29.5 percent increase in robot-production firms. My dynamic event-study analysis indicates that the policy effect persists and amplifies over time.

Second, I document significant heterogeneous impacts of the subsidy on firms of different size. More specifically, although the subsidy is designed to be uniform across firms in most of the cases, it significantly improve the financial performance of larger firms at the cost of deteriorating firm dynamics in the whole industrial sector. On the intensive margin, larger manufacturing firms are the major beneficiaries of this subsidy policy. After the policy introduction, there is a 6.4 percent rise in total assets, a 7.8 percent increase in total revenue and a 5.8 percent increase in total employment of major industrial enterprises.[4].

On the extensive margin, I find the subsidy has no significant impact on the total number of major industrial enterprises. Moreover, the introduction of the subsidy indeed significantly depresses new firm entry by around 14.0 percent. The dynamic SDID results indicate the effects intensify over time. Combining these two findings, I argue that the subsidy improves the financial performance of major industrial enterprises on the intensive margin, at the cost of reducing firm dynamics on the extensive margin. Larger manufacturing firms, which already have the advantages that come with size, can further amplify these advantages with easier access to robots. That further contributes to expansion of their market shares, which crowds out the entry of new firms.

Motivated by the empirical findings, I carry out the second step of the paper and employ a simple conceptual framework to account for the main empirical findings as well as to elucidate the efficiency trade-offs. The model incorporates borrowing costs (Hsieh and Klenow, 2009; David and Venkateswaran, 2019) into a task-based framework (Acemoglu and Autor, 2012; Acemoglu and Restrepo, 2018). Since financial frictions generally suppress the use of capital and thus automation, firms facing greater financial constraints tend to adopt automation

[4]Major industrial enterprises are defined as firms with annual turnovers exceeding twenty million CNY (around three million USD) According to the major industrial enterprise database, these firms typically fall within the top 10 to 20 percent of the turnover distribution.

levels that are below the efficient automation level of firms that are financially unconstrained. This ex-ante difference in the extent of financial constraints also implies that a uniform robot subsidy will have differential effects across firms depending on the cost of finance. Less financially constrained firms are likely to allocate a larger portion of their production tasks to industrial robots, enabling them to significantly reduce their marginal costs under a uniform subsidy. This contributes to increased market share, turnover, capital usage and employment for these firms. Conversely, more financially constrained firms, despite benefiting from the reduced marginal costs due to the subsidy, experience smaller cost reductions relative to the aggregate price decrease. Consequently, these firms suffer from the loss of market share and profitability, and are at risk of being squeezed out of the market in the absence of a substantial aggregate demand promotion.

The efficiency analysis reveals that financial frictions affect overall productivity through two main channels: mean automation depression and automation dispersion. Mean automation depression captures the inefficiency caused by financial frictions, which raise the cost of capital above its shadow (efficient) level and thus reduce firms' incentives to adopt robots. As a result, the economy's mean level of automation falls below the socially optimal level. Automation dispersion, on the other hand, captures the inefficiency arising from deviations in individual firms' automation levels from the social mean. I identify three new channels through which automation dispersion impacts overall productivity: the amplification of conventional marginal product of capital (MPK) wedges, excessive factor usage and the facilitation of individual productivity gains.

The analytical framework indicates that a uniform robot subsidy helps to address mean automation depression but unambiguously exacerbates automation dispersion. While such a subsidy can partially offset factor price distortions caused by financial frictions, it disproportionately benefits larger firms, thereby widening automation gaps across firms.

Finally, to carry out the third step and be able to gauge the dynamic impact of the robot subsidy in China, I incorporate the simple static model into a dynamic heterogeneous firm framework with endogenous occupation choice and capital accumulation. Reflecting discussions on capital misallocation due to dynamic MPK wedges (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Gopinath et al., 2017; Da-Rocha et al., 2023), I endogenize borrowing costs by linking them to heterogeneous entrepreneurs' asset positions (Moll, 2014; David and Venkateswaran, 2019). This approach reveals a new dynamic mechanism, through which automation exacerbates capital misallocation. Consistent with Moll et al. (2022), my findings show that a robot subsidy effectively promotes industrial adoption of robots, reducing wage income while enhancing capital returns and entrepreneurial profits. These dynamics intensify capital accumulation disparities among households, leading to increased borrowing cost dispersion and further aggravating capital misallocation.

I calibrate the benchmark model to match the productivity distribution, financial frictions and industrial robot density in China's industrial sector in 2010. The model indicates that the implementation of a robot subsidy of 20 percent in the 2017 industrial context results in a 65 percent increase in industrial robot demand and a 1.23 percent increase in output. The aggregate effect masks significant differences across firms: the top 10 percent of entrepreneurs (by turnover) experience improvements in turnover, capital expenditure, employment and profit of 5.34 percent, 22.67 percent, 2.94 percent and 6.84 percent, respectively. Conversely, these measures decline by 1.72 percent, 0.48 percent, 0.85 percent and 1.15 percent for the bottom 50 percent of entrepreneurs (by turnover). Overall, a 20 percent robot subsidy leads to a 1.27 percent reduction in the number of entrepreneurs.

Regarding efficiency implications, my dynamic framework shows that a uniform robot subsidy effectively narrows the gap between the mean and socially optimal automation levels: a 20 percent subsidy increases the mean automation level from 36 percent to 58 percent of the socially optimal level. However, it also significantly increases automation dispersion, with the standard deviation rising by 49 percent. While a subsidy enhances output, it reduces total factor productivity (TFP) by 2.40 percent. In general, my model shows that a uniform robot subsidy could improve social welfare (measured in utilitarian approach) by around 0.23 percent when its magnitude is below or equal to 10 percent, while it starts to damage social welfare when its magnitude goes above 20 percent.

In examining the impact of dynamic misallocation, this study finds that a uniform robot subsidy amplifies capital accumulation dispersion by reducing labour income, while increasing capital returns and entrepreneurial income. Controlling for the dynamics of asset position distribution can mitigate the divergence between wage earners and capital return earners, resulting in smaller MPK wedges and reduced TFP loss from a subsidy. Under a 20 percent robot subsidy scenario, this implies that the output gain could increase by an extra 0.37 percent.

Related Literature My study contributes to three strands of literature. First, it adds to the empirical (Bernini and Pellegrini, 2011; Cerqua and Pellegrini, 2014; Neumark and Simpson, 2015; Cerqua and Pellegrini, 2017; Howell, 2017; Zwick and Mahon, 2017; Kalouptsidi, 2018; Criscuolo et al., 2019; Lane, 2022; Dechezleprêtre et al., 2023; Incoronato and Lattanzio, 2023; Banares-Sanchez et al., 2023) and theoretical research (Buera et al., 2021; Choi and Levchenko, 2021; Cerrato, 2024) on industrial policies. In line with the recent trend of rethinking the role of industrial policies and the growing consensus that well-designed policies can foster innovation and economic development (Aghion et al., 2015; Juhász et al., 2023), I assess the potential trade-offs of industrial policies. Specifically, I examine how China's large-scale and aggressive industrial policy that promotes industrial robot adoption addresses under-investment in technology while potentially exacerbating disparities in technology adoption across firms.

Second, I contribute to the theoretical literature on endogenous automation adoption (Acemoglu and Autor, 2012; Acemoglu and Restrepo, 2018; Moll et al., 2022) and policy interventions in automation. While many studies (Acemoglu et al., 2020; Beraja and Zorzi, 2022; Costinot and Werning, 2023) argue that robot adoption should be taxed due to its tendency to exacerbate inequality across different types of agents (e.g., between capital owners and workers, or between skilled and unskilled workers), a growing body of work highlights that restricting robot adoption could hinder long-term growth and innovation (Prettner and Strulik, 2020; Gasteiger and Prettner, 2022; Guerreiro et al., 2022) and well-designed robot subsidy can indeed be welfare-improving (Caselli and Manning, 2019; Thuemmel, 2023) In contrast to much of the existing literature, which focuses on inequality between agents, my study shifts the focus to inequality between firms. I investigate how robot subsidies lead to uneven automation adoption across firms and analyze the associated efficiency and productivity implications.

Third, my study engages with the extensive literature on financial frictions and their interaction with technology adoption and industrial policy (Caselli and Gennaioli, 2005; Buera et al., 2013; Reis, 2013; Midrigan and Xu, 2014; Gopinath et al., 2017; Itskhoki and Moll, 2019). Specifically, this research is among the first to explore how financial frictions influence endogenous automation. In terms of efficiency, I examine how automation exacerbates productivity losses caused by static capital misallocation, as documented in the literature initiated by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Additionally, this study echoes the later literature on dynamic capital misallocation (Gabler and Poschke, 2013; Asker et al., 2014; Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Peters, 2020; Da-Rocha et al., 2023). More specifically, Moll et al. (2022) demonstrates how automation amplifies wealth inequality through capital accumulation. My study incorporates a dynamic perspective to reveal how endogenous automation intensifies dynamic capital misallocation by reducing labour income and increasing capital returns.

The remainder of this paper is structured as follows. Section 2 provides an overview of the institutional background. Section 3 introduces the data used in the study, along with descriptive statistics, and details the identification methods employed to estimate the economic impacts of introducing robot subsidies. Sections 4 discusses the effectiveness of subsidies in promoting robot-related activities, and Section 5 discusses the responses of the industrial sector to such subsidies. Section 6 provides a simple framework to probe into the mechanism behind the observed patterns and the efficiency and productivity implications of a uniform robot subsidy. Section 7 embeds the simple model into a dynamic framework with heterogeneous entrepreneurs, so as to quantify the implications on macro variables and efficiency measures. Section 8 offers concluding remarks.

2 Institutional Background

2.1 Strategic Importance of Subsidizing Robots in China

The strategic emphasis on robot integration within China's manufacturing sector marks a pivotal shift in industrial policy. Launched in 2015, *Made in China 2025* underscores the pivotal role of industrial robots in the country's industrial strategy. This pioneering policy gives a target for robot density, aiming for 100 units per 100,000 workers by 2020. Advancing this agenda, the *14th Five-Year Plan for Robotics Industry Development*, introduced in 2021, articulates a more ambitious goal: to boost robot density to 500 units per 10,000 workers by 2025. Despite global concerns over the potential displacement of labour stemming from more extensive adoption of robots, the Chinese government persistently advocates for a substantial expansion in the use of robots.

This strategic push has catalyzed remarkable growth in the robotics industry, evidenced by both surges in sales of robots and expansions in robot uses. Data presented in the Table 1, sourced from the International Federation of Robotics, show that, in 2022, China's installation of new industrial robots reached 290,300 units. This figure constitutes approximately 53% of the worldwide installation of industrial robots for that year. At the same time, the total stock of robots in China reached around 1.5 million units by 2022, making up about 38% of the global industrial robot stock. *Made in China 2025* sets forth, in 2015, China's ambition to manufacture 100,000 domestically branded industrial robots.

Table 1: Annual Robot Installation and Operational Robot Stocks in China

	Robot Installation:			**Robot Stocks:**			**Robot Density:**	
Year	Value (1,000 units)	Share (%)	Rank	Value (1,000 units)	Share (%)	Rank	Value (units/10,000 workers)	Rank
1995	0.00	0.00	–	0.00	0.00	–	–	–
2000	0.38	0.39	16	0.93	0.12	23	–	–
2005	4.46	3.71	9	11.56	1.26	11	–	–
2010	14.98	12.40	5	52.29	4.94	6	–	–
2015	68.56	27.02	1	256.46	15.72	2	49	–
2016	96.50	31.76	1	349.47	19.02	1	68	–
2017	156.18	39.08	1	501.19	23.58	1	97	21
2018	154.03	36.48	1	649.45	26.62	1	140	20
2019	139.86	36.71	1	782.73	28.67	1	187	15
2020	168.40	43.85	1	943.22	31.08	1	246	9
2021	268.20	51.88	1	1197.89	34.45	1	322	5
2022	290.30	52.50	1	$\approx$ 1500.00	38.42	1	392	5

Note: (1) The data is from International Federation of Robotics (IFR); (2) 'Robot Installation' refers to the number of new industrial robots installed during the year, 'Robot Stock' refers to the total number of existing operational industrial robots at the end of a year, while 'Robot Density' refers to the number of robot stock per 10,000 employees in the manufacturing industry; (3) The 'Share' columns show ratios of values of the above indicators to the world totals, the 'Rank' columns show the China's rank within all countries; (4) In 2022, top five countries in terms of robot density are South Korea (1012), Singapore (730), Germany (415), Japan (397) and China (392).

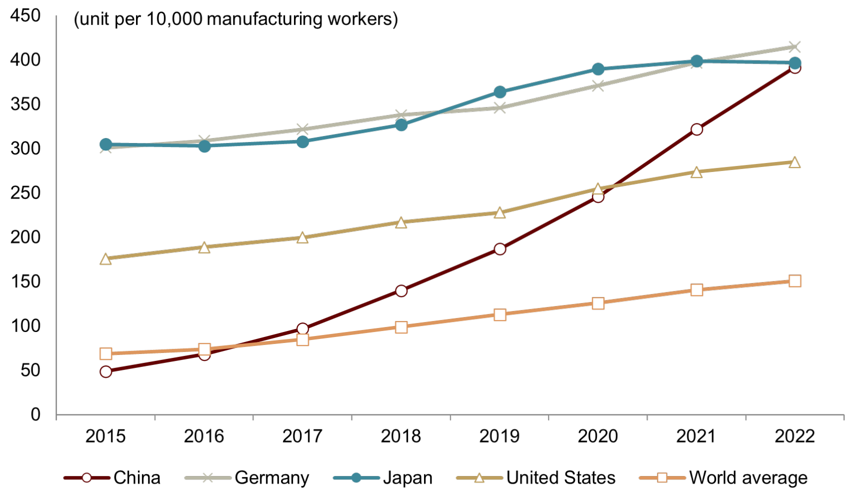


Figure 1: Cross-Country Trends in Industrial Robot Densities

Note: (1) The data is from International Federation of Robotics (IFR); (2) The world average refers to the averaged robot density of 75 countries and regions around the world.

2.2 Demand-Side Subsidy Policy in China

While *Made in China 2025* and the *14th Five-Year Plan* lay out the national strategy, the actual deployment of the individual robot subsidy policies predominantly falls under the jurisdiction of local governments, resulting in significant regional variation. Bai et al. (2020) provides a description of how local authorities are incentivized to carry out national strategies. In this study, I focus on the demand-side robot subsidy policies, which incentivizes manufacturers to acquire or lease robots.[5] These policies typically offer subsidies covering 5% to 30% of the total cost or investment associated with purchasing or leasing robots. Typically, there are no stringent eligibility criteria, allowing a broad range of enterprises to benefit from such subsidies. Meanwhile, there is a tendency for some municipalities to introduce local preference clauses, which might restrict subsidies to robots manufactured within the locale or incrementally increase subsidies for the acquisition of robots produced locally.

[5] I do not focus on supply-side subsidies that target the innovation of robotics technology and manufacture of industrial robots.

Measuring Demand-Side Subsidy Policies

Nationally, policy directives are clearly defined. At the local level, however, there is a need to categorize and identify specific industrial policies, particularly distinguishing between those with and without concrete and executable subsidization measures. To pinpoint policies encouraging the adoption of robots, I use data from the PKULaw dataset of laws and regulations, which documents laws, regulations and administrative documents issued by different levels of authorities in China since 1949.

The dataset includes details, such as the policy's title, its issuing department, date of issuance, the date it came into effect and the original contents. I extract the original texts of the policies, which make up the specifics of each regulation. Using a text-recognition algorithm, I categorize the policies by type, specifically concentrating on those that offer direct financial subsidies for purchasing industrial robots.

A policy qualifies as being related to robot subsidies if it meets three specific conditions across three successive paragraphs. First, the policy must contain keywords related to robotics, automation, smart devices or smart technology, highlighting its relevance to the adoption of robots. Second, it must outline a detailed and executable subsidy scheme, allowing for the verification of the extent of financial assistance provided for each acquisition or lease. Finally, the document must explicitly state that the financial assistance is a subsidy, enabling the algorithm to classify it as a subsidy policy. This approach allows me to confine the study to municipal-level robot-related industrial policies with concrete subsidization measures.

Following the above procedures, I successfully identify 244 municipal-level robot-related subsidy policies between the years 2014 and 2023.

Characteristics of Demand-Side Subsidy Policy

In analyzing the eligibility criteria for robot subsidy policies, I identify three key characteristics. First, the majority of subsidies provide uniform accessibility and intensity across firms without specific prerequisites, a feature I refer to as non-exclusiveness. Specifically, approximately 85% of subsidies impose no restrictions on the size or qualifications of applicants. In contrast, a smaller portion - about 7.5% - requires a minimum investment threshold of over 15 million USD. Additionally, only 1.1% of subsidies are allocated based on firm size, indicating minimal emphasis on organizational scale. Finally, 6.3% of subsidies are strategically targeted at firms selected by local governments, suggesting a targeted approach within the policy framework. While this targeting could raise concerns about firm selection due to special deals, as documented by Bai et al. (2020), I believe such concerns are minimized in this context due to the small number of targeted cases.

Second, local preferences are common in these subsidies. Around 42.9% provide exclusive financial support to buyers of robots produced by local manufacturers, while approximately 28.1% offer progressive support to locally produced robot equipment. This characteristic establishes a critical link between demand-side subsidies and local robotics industry activities: the increase in robot demand resulting from the subsidy tends to remain local, contributing to the expansion of the local robotics industry.

Third, the magnitude of local government support is substantial. Approximately 82% of subsidies offer financial support exceeding 10% of the purchase price or rental fee of industrial robot equipment. The average subsidy rate is around 17.5%, which is likely to have a significant impact on the manufacturing sector. For reference, with an average unit price of 40,000 USD for industrial robot equipment, this implies a subsidy of 8,000 USD per unit.

2.3 Subsidized Municipalities in China (2014-2023)

As Figure 2 demonstrates, there has been a significant increase in the number of municipalities adopting demand-side robot subsidies between 2014 and 2023. In 2014, only two municipalities had implemented such subsidies. By 2023, the number has risen to 93, representing approximately 32% of all municipalities. Figure 3 provides a general picture of the geographic distribution of robot subsidy implementation and the number of applications for robotics patents. Two key observations emerge from this figure. First, the introduction of a robot subsidy is effective in promoting applications for robotics patents in the local areas - shown by the fact that the municipalities with red borders (delineating robot subsidies) are more likely to have darker shading (delineating a greater number of patent applications) in subsequent years. Second, endogeneity of subsidy introduction can also be observed. In 2016, a distinct cluster of early adopting municipalities is characterized by their pioneering adoption of industrial robots and the strategy of replacing labour with machines.[6] Since those provinces are already more economically developed and tend to be home to a more mature robotics industry, this pattern suggests that the implementation of robot subsidies tends to be endogenous in observable factors, such as fiscal capacity and prevailing industrial structures, as well as in unobservable factors.

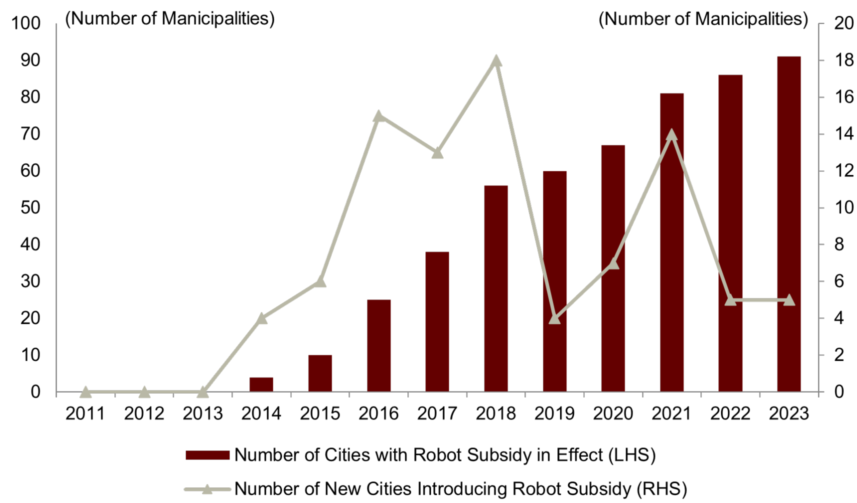


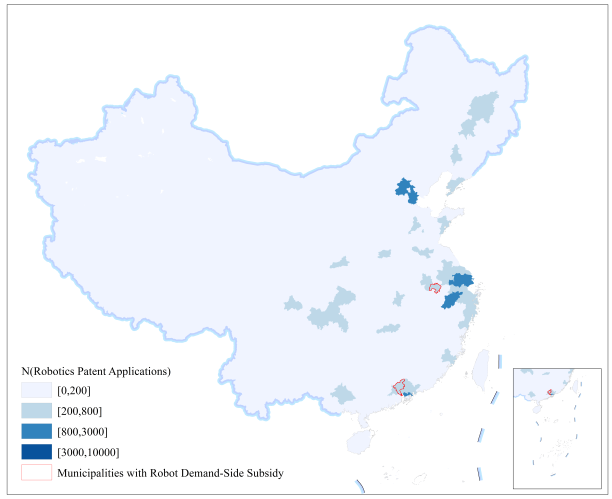
Figure 2: Number of Municipalities That Introduced Robot Demand-Side Subsidy

Selection Criteria

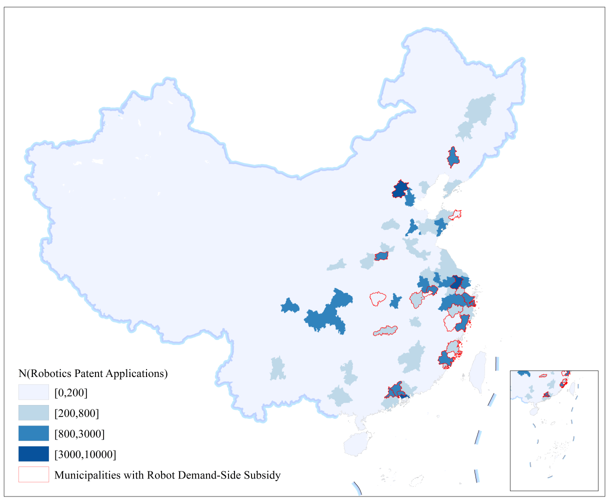
Table 2 reports the relationship between municipal characteristics and the adoption of robot subsidy policies, focusing on six key attributes: fiscal capacity, educational resources (specifically vocational schools), industrial enterprise statistics, foreign investment, economic development and labour market conditions. My analysis highlights the role of fiscal capacity, educational resources, the presence of industrial enterprises and foreign investment in encouraging local government support on industrial robots. More specifically, these factors suggest that local governments tend to tailor their subsidy policies based on their financial

[6]The replacing labour with machines policy in China is part of a broader strategy to modernize the country's manufacturing sector by promoting automation and the use of industrial robots. The policy, which gained momentum around 2014, encourages firms, particularly in labour-intensive industries, to adopt robotics and automated systems to address rising labor costs, improve efficiency, and enhance product quality.

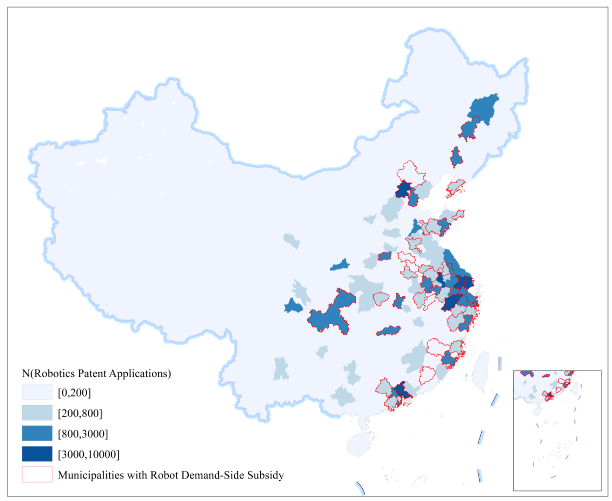
(a) 2010



(b) 2014



(c) 2016



(d) 2018

Figure 3: Geographical Distribution of Robot Demand-Side Subsidy

Note: (1) Municipalities marked with red borders are those that have introduced robot demand-side subsidy by 2014, 2016 and 2018; (2) The shadiness of a municipality represents the number of robotics patent applications in the local area; (3) The maps provide a rudimentary illustration of how robot demand-side subsidies promote robot-related innovation activity in local areas: municipalities that introduced robot subsidy tend to hold larger number of robotics patent application in the subsequent years; (4) In practice I eliminate autonomous regions Xinjiang and Tibet and special administrative regions Hong Kong, Macau and Taiwan due to data limitation. There is a total of 282 municipalities left, which account for 1,233.75 million residents or around 92.2% of national population in 2010.

wherewithal and the readiness of local industries to integrate robotics into their operations. This aligns with the observation in Figure 3 that wealthier provinces in southeast China are often at the forefront of the implementation of demand-side robot subsidies.

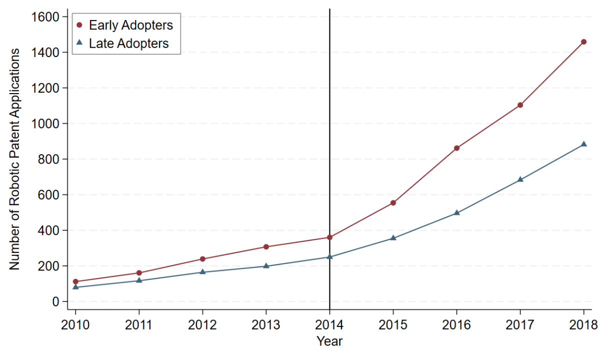
Table 2: Determinants of Demand-Side Policy Implementation in Municipalities

(Lagged by One Year)	(1)	(2)	(3)	(4)	(5)	(6)
Fiscal Revenue	0.127**					0.130**
	(0.063)					(0.059)
No.(Vocational Schools)		0.053				0.071**
		(0.035)				(0.033)
Current Asset			0.035			0.022
			(0.036)			(0.037)
No.(Large Manufacturing Firms)			0.076*			0.091**
			(0.043)			(0.041)
Foreign Investment				0.028**		0.022*
				(0.014)		(0.013)
GRP per capita					0.059	−0.062
					(0.088)	(0.094)
Share of Secondary Industry					−0.001	−0.005*
					(0.003)	(0.003)
Private Sector Employment					0.015	0.012
					(0.022)	(0.021)
Average Wage Rate					0.016	0.032
					(0.090)	(0.087)
R-squared	0.543	0.541	0.543	0.542	0.540	0.546
Number of observations	2,250	2,250	2,250	2,250	2,134	2,134
Fixed effects						
Year	X	X	X	X	X	X
Province time trend	X	X	X	X	X	X

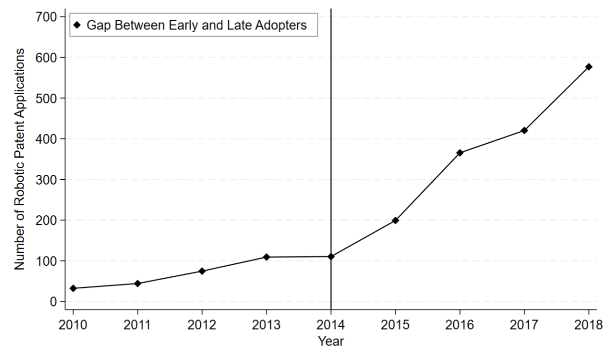
***Note*:** (1) All regressions control for ten distinct categories of attributes, while the others are not statistically significant; (2) Standard errors are clustered at the municipal level; (3) All observations are weighted by municipal population in 2011, weights per year represent millions of residents; (4) *, **, and *** respectively indicates significance at the 10%, 5%, and the 1% significance level.

Despite the possibility that the introduction of robot subsidies could be correlated with city characteristics, I argue that endogeneity is not a significant concern in this study for two key reasons. First, the results from the two-way-fixed-effects regressions included in the robustness checks show no significant differences between treated and control municipalities, both in terms of magnitudes and statistical significance. This finding implies that, although it is plausible that the introduction of the subsidy could be endogenous to city characteristics, there is no significant correlation between the subsidy and the outcomes of interest.

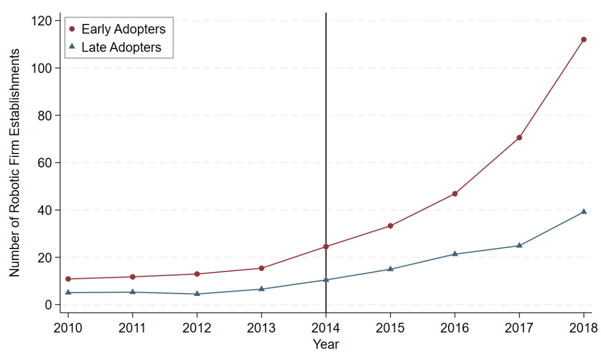
More importantly, the key identification assumption of my empirical framework is that the **timing** of subsidy introduction across municipalities is uncorrelated with the outcomes of interest. This assumption is supported by the descriptive Figures 4 for robotics patent applications and robotics firm entries. Sub-figure (a) of Figure 4 compares the average number of robotics patent applications for early adopters (municipalities that introduced the subsidy by 2016) and late adopters (those that introduced it after 2017). The trends for early and late adopters are highly parallel before 2014, when the first robot subsidy was introduced. After 2014, the differences between early and late adopters begin to diverge, suggesting a significant impact of the subsidy. This pattern is more pronounced when directly examining the gap between the two groups, as illustrated by sub-figure (b) of Figure 4, with a clear kink around 2014. A similar trend is observed in the number of robotics firm entries, as shown in sub-figures (c) and (d) of Figure 4, providing further evidence to support my key identification assumption.



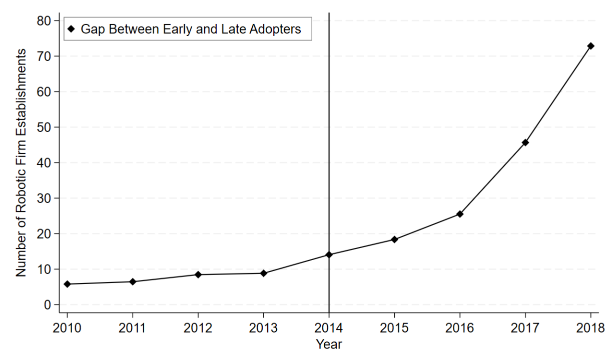
(a) Robotics Patents (Average)



(b) Robotics Patents (Gap)



(c) Robotics Firm Establishments (Average)



(d) Robotics Firm Establishments (Gap)

Figure 4: Time Trends of Outcomes of Interest of Early and Late Adopters

Note: (1) Sub-figure (a) presents the time trends of the average number of robotics patent applications for early and late adopters; (2) Sub-figure (b) illustrates the gap in the average number of robotics patent applications between early and late adopters; (3) Sub-figure (c) shows the time trends of the average number of robotics firm establishments for early and late adopters; (4) Sub-figure (d) depicts the gap in the average number of robotics firm establishments between early and late adopters; (5) Early adopters denote the 23 municipalities that introduced robot demand-side subsidy by 2016, while late adopters denote the 40 municipalities that introduced robot demand-side subsidy after 2017.

3 Data and Research Design

3.1 Data and Descriptive Results

For the preliminary results, I concentrate on two key outcome categories: robotics activities and financial performances and firm dynamics of industrial enterprises. Detailed descriptions of patent application, business registration and major industrial enterprise datasets are given next. Table 3 presents the descriptive statistics for these dependent variables.

Robotics Patent Applications. I obtain the universe of patent application between 2010 and 2018 in China from China National Intellectual Property Administration (SIPO). Robotics patents are identified through two distinct approaches. Firstly, patents containing specific keywords related to industrial robots, such as 'robot', 'robot arms', and 'AGV' in their descriptions are included. Secondly, patents featuring terms associated with robot-related modules, like 'servomotor' and 'reducer', are also considered. All patents categorized under Design Patent are excluded from this classification.

Robotics Company Registration I obtain the universe of business registration records between 2010 and 2018 in China from the National Enterprise Credit Information Publicity System. The identification of robotics companies involve pinpointing manufacturing firms with keyword 'industrial robot' in their primary business activities. A more detailed focus is applied to firms operating in specific sectors such as machinery, electronic and electric manufacturing, as well as information technology and research and development services, given their direct relevance to the robotics industry. Moreover, I confine our study to private enterprises only.

Industrial Business Registration. Except for robotics companies, my study also concentrate on analyzing new firm entries within the manufacturing sector. This is further narrowed down to detailed industries that are more likely to be impacted by the adoption of industrial robots, including machinery, automobile, electronic and electric production sectors. For a robustness check, the effects on all business registrations and the tertiary sector are also examined.

Table 3: Descriptive Statistics

	Treated	**Controls**	**Δ(T-C)**	**C/T**
Panel A: Robotics Patent Application (2010-2018)				
All Patents	19,045.53	2,720.50	16,324.83	14.28%
Robot Patents	279.74	29.20	250.54	10.44%
Robot Module Patents	117.41	24.86	92.55	21.17%
Robotics Patents	483.24	67.27	415.97	13.92%
Panel B: Number of Newly-Established Robotics Enterprises (2010-2018)				
Manufacturing	26.18	2.55	23.63	9.74%
Machinery	12.88	1.26	11.62	9.78%
Electronic	2.63	0.16	2.47	6.08%
Electric	1.95	0.19	1.76	9.74%
Panel C: Number of Newly-Established Manufacturing Enterprises (2010-2019)				
All Firms	73,060.91	24,053.46	49,007.45	32.92%
Tertiary Sector	59,268.34	18,731.00	40,537.34	31.60%
Manufacturing	5,438.92	1,426.14	4,012.78	26.22%
Machinery	682.71	119.11	563.60	17.45%
Automobile	112.05	25.92	86.13	23.13%
Electronic	187.05	15.55	171.50	8.31%
Electric	246.94	31.79	215.15	12.87%
Panel C: Number of Newly-Established Manufacturing Enterprises (2011-2020)				
Counts	2.81	0.83	1.98	29.54%
Turnovers	798.19	232.39	565.80	29.11%
Total Assets	761.33	219.27	542.06	28.80%
Employments	901.83	209.46	692.37	23.23%
Number of Municipalities	63	219		

Note: (1) Panel A is from China National Intellectual Property Administration (SIPO). Panel B and C are from business registration data of National Enterprise Credit Information Publicity System. Panel D is from major industrial enterprise data collected from provincal- and city-level statistic yearbooks; (2) The treated group includes 63 municipalities that have introduced robot subsidy between 2010 and 2020, while the control group covers all remaining 219 municipalities; (3) 'Robot Patents' refers to patents for entire robotic assemblies, 'Robot Module Patents' refers to patents on essential components for robot production, such as reducers, and 'Robotics Patents' refers to all patents related to robots (including robot patents and robot module patents); (4) 'Major Industrial Enterprises' are defined as those with an annual turnover of over three million USD; (5) The units of major industrial enterprises' financial performance metrics are as followed: 'Counts' are measured in thousands, 'Turnovers' and 'Total Assets' are measured in billion CNY and 'Employments' are measured in thousand employees.

Major Industrial Enterprises To assess the financial performance of large firms within the manufacturing sector, I utilize data from the major industrial enterprises dataset compiled from provincial-level statistical yearbooks spanning 2011 to 2020. Notably, the criteria for defining major industrial enterprises (also known as above-designated-scale industrial enterprises) were revised in 2010, raising the threshold from an annual turnover of approximately five million CNY (around 700 thousand USD) to twenty million CNY (around three million USD). Consequently, our analysis focuses on the period post-2011 to circumvent potential distortions arising from this definitional change. Specifically, I examine metrics such as firm counts, turnovers, total assets, and employment levels. Robustness checks are conducted using additional measures like profits and fixed assets, detailed in the appendix, although these are excluded from the main analysis due to concerns regarding data quality.

3.2 Empirical Strategy

OLS for policy selection

I explore the potential endogeneity of robot demand-side subsidies by examining the relationship between the timing of policy implementation and the existing characteristics of municipalities. I estimate the following OLS regression model:

$$P_{it} = \alpha + \sum_{l=1}^{3} \beta_l X_{i,t-l} + \phi_{jt} + \lambda_t + \epsilon_{it}.$$

Here, P_{it} is a dummy variable that equals one if municipality i has introduced robot demand-side subsidy by year t. In this regression, I control for temporal influences induced by national policies, like the introduction of Made in China 2025 initiative, through year fixed effects λ_t, as well as those induced by provincial policies through province-by-year fixed effects ϕ_{jt}.

Our core explanatory variables are the lagged municipal-level characteristics, $X_{i,t-l}$, which are observed one to three years prior to the policy implementation. $X_{i,t-l}$ encompasses ten distinct categories representing various municipal-level attributes of interest. The coefficients β_l capture the correlation between these municipal characteristics in the preceding years and the introduction of the robot demand-side subsidies. By including lags, I assess how ex-ante characteristics of municipalities correlate with the adoption of robot-related policies.

Synthetic Difference-in-Differences for policy impacts

In studying the impacts of the policy, I adopt the Synthetic Difference-in-Differences (SDID) approach, developed by Arkhangelsky et al. (2021), as my main identification strategy. The underlying econometric model for SDID essentially applies a weighted two-way fixed effect regression (TWFE), detailed as follows:

$$(\hat{\beta}, \hat{\alpha}, \hat{\gamma_i}, \hat{\lambda_t}) = \underset{\beta,\alpha,\lambda_i,\gamma_t}{\arg\max} \left\{ \sum_{i=0}^{N} \sum_{t=0}^{T} (Y_{it} - \alpha - \beta P_{it} - \gamma_i - \lambda_t)^2 \hat{\omega}_i \hat{\mu}_t \right\},$$

where P_{it} represents the treatment variable that captures the introduction of robot demand-side subsidy in municipality i. Y_{it} denotes a set of outcomes of interest in municipality i in year t. It can be classified into two categories: **robotics industry performances** (number of robotics patent application, number of newly-established robotics firms) and **industrial sector performances** (number of newly-established firms, and turnover, employment and total asset of major industrial enterprises).

The SDID approach differs from the standard TWFE regression by including two weights: $\hat{\omega}_i$ denotes the unit weight on city i so as to roughly match pre-treatment trends of control units with those for the treated ones; $\hat{\mu}_t$ denotes the time weight on year t to balance the pre- and post-treatment periods for the control unit.

My choice of methodology is motivated by recent discussions on the properties of the staggered Difference-in-Differences (DID) approach, which raised concerns about potential biases due to the weighting problem, as highlighted by Borusyak et al. (2024). Moreover, the potential endogeneity of subsidy policy implementation within a municipality also imposes potential challenge in utilizing traditional DID practices. In light of these issues, I argue that the SDID method is particularly advantageous for our empirical setting and could provide more accurate and reliable estimates for the following two reasons.[7]

First, the SDID framework constructs counterfactuals for treated municipalities by cal-

[7] For some other applications of the SDID, Banares-Sanchez et al. (2023) use SDID to address the selection problem of industrial policy on solar panel industry in China and Hu and Wang (2024) use SDID to address the selection problem of Flood Detention Basin policy in China.

culating weighted averages from an extensive pool of potential control municipalities. The use of synthetic weights to construct a counterfactual group, as suggested by Abadie et al. (2010), effectively addresses concerns related to the weighting problem inherent in traditional TWFE DID approach. SDID closely aligns with the pre-treatment characteristics of the treatment group, significantly enhances the credibility of causal inferences.

Second, the decision to implement subsidy policies might be influenced by observable factors like local economic development, fiscal capacity, and the prevailing industrial structure, as well as unobservable elements. While I can control for these observable characteristics, it is challenging to mitigate pre-treatment differences between treated and control municipalities arising from unobservable features. Furthermore, the distribution of industrial subsidies to firms within a municipality might be influenced by specific firm characteristics, making it infeasible to assume that these subsidies are randomly assigned. The use of synthetic weights addresses potential threats to exogeneity by ensuring that the counterfactual group mirrors the pre-treatment outcomes of the treatment group. This alignment is critical for upholding the parallel trends assumption, which is foundational for the validity of DID estimates. The SDID method's capacity to generate a closely matched synthetic control group thereby reinforces this assumption, enhancing the robustness and credibility of causal inferences drawn from the analysis. I will also check the robustness of results based on traditional two-way-fixed-effects (TWFE) estimators, the heterogeneous treatment effects model proposed by De Chaisemartin and d'Haultfoeuille (2020), and the DID method for multiple time periods as outlined by Callaway and Sant'Anna (2021).

In light of the staggered introduction of municipal subsidy policies over time, I implement a cohort-by-cohort approach in Banares-Sanchez et al. (2023). The methodology unfolds in three stages: Firstly, cities are categorized into two groups: a treated group and a never-treated group (which serves as the control group). Within the treated group, cities are further organized into distinct cohorts based on the year they first implemented robot subsidy policies. Secondly, using the SDID estimation, I determine the cohort-specific Average Treatment on the Treated (ATT). In this step, cities from each cohort function as a treatment group, while never-treated cities constitute the control group. The final step aggregates the cohort-specific ATTs to deduce an aggregate ATT for the entire sample.

4 Effectiveness of Subsidy Policy

The initial step of my analysis is to assess whether the demand-side policy effectively boosted robot utilization. Although direct municipal-level measures of robot utilization are unavailable, the local preference characteristic outlined in Section 2.2 suggests that the increased demand for robots largely remains within local areas. Consequently, I evaluate the impact of robot subsidies from two supply-side perspectives. First, I examine the influence of demand-side subsidies on innovation within the robotics sector, as indicated by an increase in robot-related patent filings. Second, I analyze the effect of these subsidies on the expansion of the robotics firm landscape. Based on my Difference-in-Differences analysis, I argue that the demand-side subsidy policy has demonstrated efficacy.

4.1 Increase in Robotics Patents

My findings reveal that the robot demand-side subsidy significantly bolsters innovation in robotics within the local areas. As illustrated in Table 4, I investigate the policy impact on the number of robotics patent application. Leveraging SDID analysis, I construct a synthetic counterfactual to determine the policy's causal effects by comparing the actual outcomes against those of the counterfactual group. This analysis confirms that the robot demand-side subsidy exclusively augments the count of robotics-related patent applications. Specifically, Column (1) shows a 13.6% increase in total robotics patent applications attributable to the subsidy. Further dissection in Columns (2) and (3) examines various segments of robotics patents: robot units and robot modules, with 'Robot Units' encompassing patents for entire robotic assemblies, and 'Robot Modules' focusing on essential components for robot production, such as reducers. These columns reveal that the demand-side subsidy brought increases of 18.7% and 13.3% in robot units and robot modules applications, respectively. Column (4) acts as a placebo test. I hypothesize that the subsidy impacts on robotics patents are not results of concurrent macro trends. This hypothesis is validated by the finding presented in Column (4) that indicates an insignificant impact of the subsidy policy on all patents.

Table 4: Aggregate ATT on Robotics Patent Applications

	Robotics Patents	Robotics Patents:		All Patents
		Robot Units	*Robot Modules*	
(in IHS)	(1)	(2)	(3)	(4)
Demand Subsidy	0.136**	0.187***	0.133**	0.030
	(0.062)	(0.068)	(0.069)	(0.049)
N(obs)	2,538	2,538	2,538	2,538
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y

Note: (1) The results is based on SDID approach; (2) The coefficient is the ATT which averages the staggered treatment effect of all cohorts; (3) Outcome variables are in Inverse Hyperbolic Sine; (4) Standard errors are clustered at municipal level; (5) *, **, and *** respectively indicates 10%, 5%, and 1% significance level; (6) 'Robot Units' refers to patents of entire robotic production and assemblies, 'Robot Module' refers to patents related to the production of essential components, such as reducers, and 'Robotics Patents' refers to all patents related to robots (including robot patents and robot module patents); (7) 'All Patents' refer to the patent application of all categories, including but not limited to robotics patents.

Figure 5 delineates the dynamic effects of subsidies on robotics patents. Each dot depicted in the figure signifies a point estimate, illustrating the differences between municipalities that received demand-side subsidies and their synthetic counterfactual groups. The estimates' approximation to zero prior to the treatment, along with their statistical non-significance, validates the precision of the synthetic group in accurately representing the counterfactual groups for municipalities. The policy start to generate immediate impact subsequent to the implementation of the robot demand-side subsidy, with the number of robotics patents in subsidized municipalities surpassing those in their counterparts. Furthermore, the effect's magnitude escalates progressively, signifying the long term and persistent impact of the demand subsidy in propelling robotic innovations. Initially, in period 0, the impact stands at approximately 7%, escalating to around 50% in three years, evidencing the sustained and amplifying influence of demand subsidies on robotic innovation.

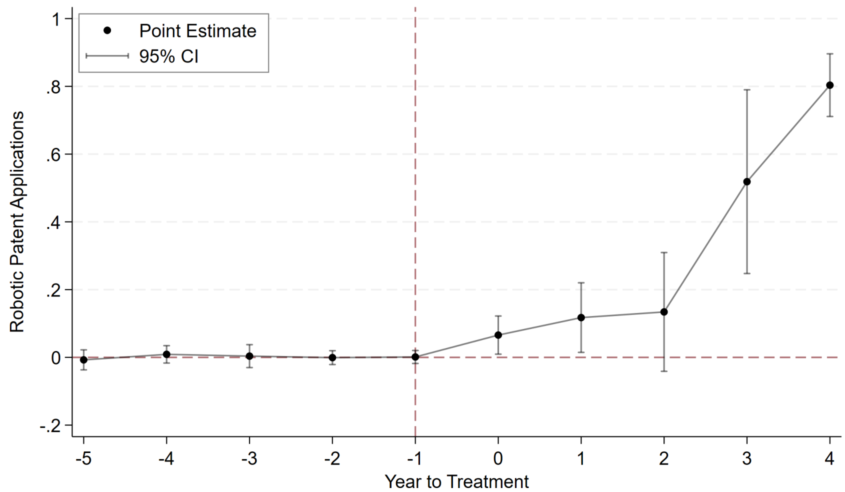


Figure 5: Dynamic Impact on the Number of Robotics Patents

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Robotics Patents' refer to all patent applications related to industrial robots and robot-related modules; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the number of robotics patents in treated municipalities is larger than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

4.2 Increase in Robotics Firm Establishment

I next examine the effects of demand-side robot subsidies on the number of robotics firms within China. Table 5 focuses on firms engaged in the manufacture of robots or robotic components. Given the concentration of robot-producing enterprises within the machinery sector, I consider Column (2) to be the notable result shown in the table. My analysis indicates that robot subsidy policies foster a 29.5% increase in the number of firms manufacturing robots within the machinery sector. Additionally, my investigation extends to enterprises involved in robot production within the electronic and electrical sectors, despite these not being their primary business focus. Table 5 indicates an increase of 26.4% and 35.6% in the number of firms within the electronic and electrical sectors, respectively. Table 6 acts as a placebo test. I hypothesize that the subsidy impacts on robotics firm entry are not results of concurrent macro trends. This hypothesis is validated by the finding presented in Table 6 that indicates an insignificant impact of the subsidy policy on all firm entry or tertiary firm entry.

Table 5: Aggregate ATT on Robotics Firm Establishments

	Manufacturing	Manufacturing:		
		Machinery	*Electronic*	*Electric*
(in IHS)	(1)	(2)	(3)	(4)
Demand Subsidy	0.295***	0.432***	0.264***	0.356***
	(0.091)	(0.108)	(0.096)	(0.092)
N(obs)	2,538	2,538	2,538	2,538
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y

Note: (1) The results is based on SDID approach; (2) The coefficient is the ATT which averages the staggered treatment effect of all cohorts; (3) Outcome variables are in Inverse Hyperbolic Sine; (4) Standard errors are clustered at municipal level; (5) *, **, and *** respectively indicates 10%, 5%, and 1% significance level; (6) 'Manufacturing' refers to all robotics firms in the manufacturing sector, 'Machinery', 'Electronic' and 'Electric' categories cover robotics firms classified into corresponding sub-industries.

Figure 6 illustrates the evolving influence of robot subsidy policies on the establishment of robotics firms across all cohort. My analysis reveals that the enactment of a robot subsidy policy catalyses a marked escalation in the establishment of robotics firms. In period 0, the quantity of robotics firms in municipalities with a robot subsidy policy increases by 50% relative to their synthetic control group counterparts, a growth that is not merely statistically significant but also of considerable economic significance. This trend persists over three years, at a relatively stable magnitude, indicating the sustained impact of the policy.

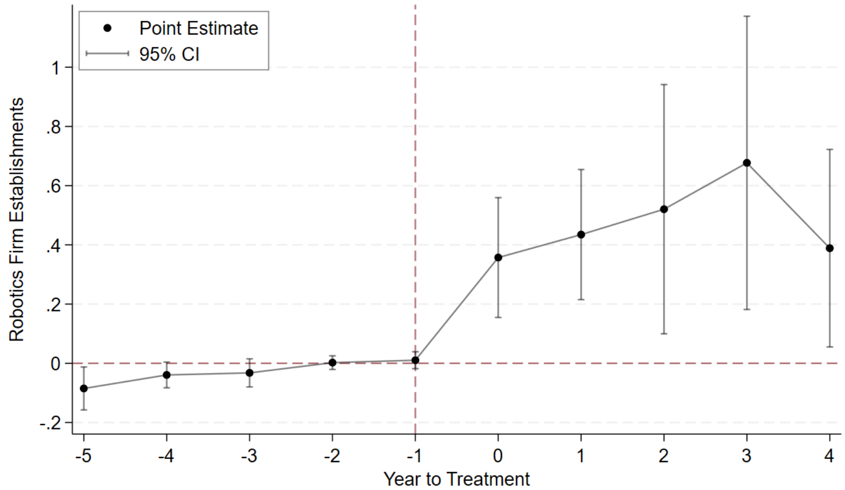


Figure 6: Dynamic Impact on Robotics Firm Establishment

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Robot Firm Entry' refers to the number of newly-established machinery-manufacturing enterprises that produce industrial robots as their major businesses; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the number of robotics firm establishment in treated municipalities is larger than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

Table 6: Aggregate ATT on Overall Business Establishments

(in IHS)	Overall	Overall	Tertiary	Tertiary
Demand Subsidy	−0.061	−0.064	−0.067	−0.063
	(0.044)	(0.042)	(0.042)	(0.045)
N(obs)	2,820	2,820	2,820	2,820
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y
Controls	N	Y	N	Y

Note:(1) The results is based on SDID approach; (2) The coefficient is the ATT which averages the staggered treatment effect of all cohorts; (3) Outcome variables are in Inverse Hyperbolic Sine; (4) Standard errors are clustered at municipal level; (5) *, **, and *** respectively indicates 10%, 5%, and 1% significance level.

4.3 Robustness Checks With Other DID Methods

Figures 7 and 8 present the results of the analysis on applications for robotics patents and the establishment of robotics firms using various DID methods. While I assert that SDID (Arkhangelsky et al. 2021) is the most appropriate for my empirical setting, I also include event-study results employing three alternative methodologies: the traditional TWFE estimators, the heterogeneous treatment effects model proposed by De Chaisemartin and d'Haultfoeuille (2020) and the DID method for multiple time periods as outlined by Callaway and Sant'Anna (2021).

Two key observations emerge from these results. First, all three methods yield post-treatment effects that are consistent with those shown in Figures 5 and 6. This consistency suggests that my primary findings are robust across different methodological approaches and not solely dependent on the SDID method. Second, the traditional TWFE estimators indicate some significant differences between treated and control municipalities, particularly at period -5. This aligns with my OLS results, which suggest that the introduction of robot subsidy policies may be endogenous to observable factors, such as fiscal capacity and existing levels of development of the robotics industry, as well as to unobservable factors. The methods proposed by De Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021) effectively render the pre-treatment trends insignificant, thereby satisfying the parallel trends assumption necessary for valid DID identification. Nonetheless, the magnitude of the point estimates remains relatively large. These findings further validate the use of SDID as my primary identification strategy, as it mitigates significant pre-treatment trends by constructing a credible synthetic counterfactual for treated municipalities using a comprehensive set of control units.

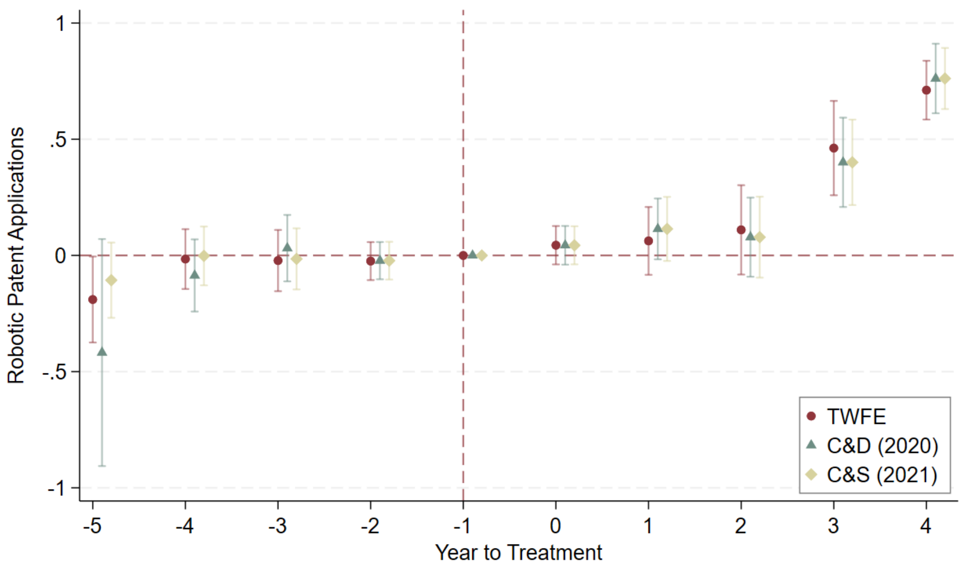


Figure 7: Event Study Robustness Check - Robotics Patent Applications

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Robotics Patent Applications' measures the IHS of municipal-level numbers of robotics patent applications between 2010 and 2018; (3) Before treatment, traditional TWFE shows slightly significant difference between treated and control municipalities in period -5, while C&D and C&S approaches help render the pre trend insignificant. That also supports the validity of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and positive estimates, suggesting the number of robotics patent application in treated municipalities becomes persistently larger than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

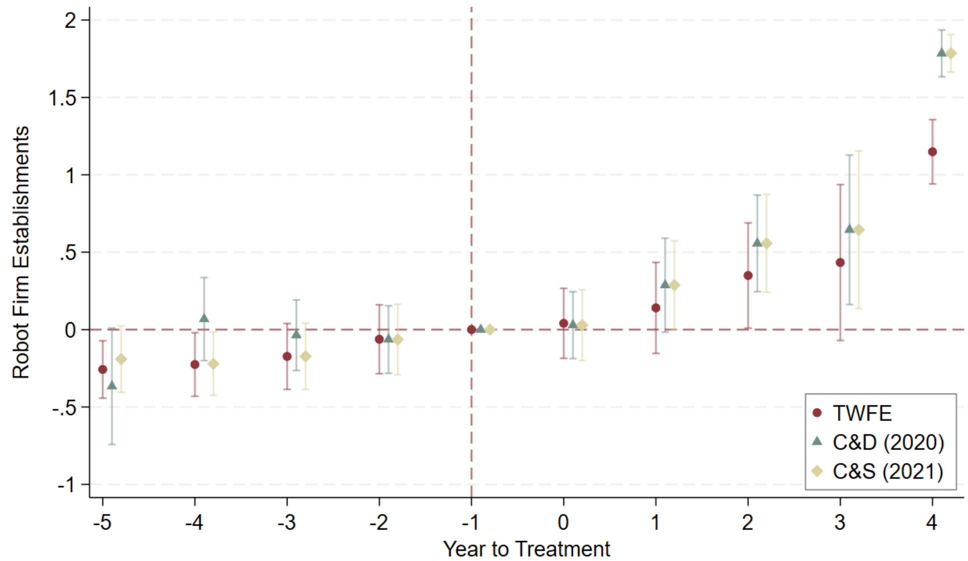


Figure 8: Event Study Robustness Check - Robot Firm Establishments

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Robot Firm Establishments' measures the IHS of municipal-level numbers of new robot firm establishments between 2010 and 2018; (3) Before treatment, traditional TWFE shows slightly significant difference between treated and control municipalities in period -4 and -5, while C&D and C&S approaches help render the pre trend insignificant. That also supports the validity of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and positive estimates, suggesting the number of new robot firm establishment in treated municipalities becomes persistently larger than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

4.4 Summary

Overall, my findings affirm that local governments in China have effectively achieved the objectives of the demand-side robot subsidy policy. Following the implementation of these policies, a significant increase in robotics-related innovation is observed, alongside an expansion in the number of firms prioritizing robot production in their operations, as shown in Table 4 and Table 5. This empirical evidence aligns with the local preference characteristic of China's robot subsidy, which confines the increase in robot demand to the local supply chain. My placebo tests in Table 4 and 6 demonstrate that the treatment does capture the policies targeting the industrial robots only, and the changes of aggregates are not results of underlying macro trends. My further robustness checks demonstrate the consistency of my findings across multiple methodologies, which underscores the validity of my results and the robustness of the conclusions.

5 Subsidy-led Disproportional Benefits Across Firms

The analysis in the previous section has validated the effectiveness of robot subsidy policies in augmenting the robot supply in the market. This section shifts focus to the demand-side reaction to such subsidies. Given that demand-side subsidies offer financial incentives for robot purchases, I explore how manufacturing firms respond to such policies. Particularly, I investigate different responses across manufacturing firms of differing sizes. My investigation is guided by two hypotheses: first, the facilitated access to robot technology incentivizes firms to enter the market; second, larger firms enjoy greater benefits from the policy due to their higher incentive and ability to substitute labour with robot technology.

My empirical analysis does not corroborate the first hypothesis, revealing a decline in the entry of new manufacturing firms subsequent to the implementation of a robot subsidy policy. Conversely, my findings support the second hypothesis. I observe that major industrial enterprises exhibit increases in employment, total assets and total turnover following the introduction of a robot subsidy policy. This contrast between the general manufacturing sector and larger firms suggests that, such policies are likely to result in an intensive margin improvement for larger firms, at the cost of extensive margin deterioration in the whole sector. Since the primary beneficiaries of such policies are indeed these larger manufacturing firms, such outcomes may imply an increase in market concentration, with the benefits of such a policy disproportionately accruing to larger firms, thereby amplifying their inherent advantages.

5.1 Decrease in Manufacturing Firm Establishment

Table 7 shows the aggregate effects of a robot subsidy policy on new firm entry across the manufacturing sector, including sub-industries such as machinery, automobile, electronic, and electrical. Our analysis reveals a general decline in manufacturing firm entries after the introduction of a robot subsidy policy. Overall, after policy implementation, the number of new manufacturing firms decreases by 14.0%. Notably, those sub-industries with greater robot penetration, such as automobile, electronic and electrical production, experience more pronounced declines. After policy implementation, the number of new firms decrease by 28.3%, 36.7% and 35.5%, respectively, in the automobile, electronic and electrical production sectors. I conduct a placebo test by applying the SDID investigation on all firms and firms in the tertiary sector, as shown in Table 6. I find that the policy does not have a significant impact on all firms and firms in the tertiary sector. This indicates that the policy only affects the manufacturing sector.

Table 7: Aggregate ATT on Manufacturing Firms Entry

(in IHS)	Manu	Machinery	Automobile	Electronic	Electric
Demand Subsidy	−0.140**	−0.190***	−0.283***	−0.367***	−0.355***
	(0.058)	(0.070)	(0.092)	(0.088)	(0.092)
N(obs)	2,820	2,820	2,820	2,820	2,820
Fixed Effects					
Year	Y	Y	Y	Y	Y
Municipality	Y	Y	Y	Y	Y

Note: (1) The results is based on SDID approach; (2) The coefficient is the ATT which averages the staggered treatment effect of all cohorts; (3) Outcome variables are in Inverse Hyperbolic Sine; (4) Standard errors are clustered at municipal level; (5) *, **, and *** respectively indicates 10%, 5%, and 1% significance level; (6) 'Manufacturing' refers to all firms in the manufacturing sector, 'Machinery', 'Automobile', 'Electronic' and 'Electric' categories cover firms classified into corresponding sub-industries.

Figure 9 illustrates the dynamic effects of a robot subsidy policy on municipalities that initiated a demand-side subsidy. The figure clearly shows a reduction in the entry of new manufacturing firms. Following the introduction of such a subsidy, there is an immediate 8% decrease in period 0. This downward trend intensifies over time, with the impact of such a subsidy reaching an approximate 70% magnitude in five years.

This striking trend suggests that a robot subsidy policy diminishes the incentive for firm entry into the manufacturing sector, possibly due to increased market concentration after the introduction of the policy. Although young and small firms are able to enjoy the benefits of a robot subsidy in absolute terms, the advantage they obtain tends to be smaller relative to that of major players in the market. Meanwhile, larger firms, already benefiting from

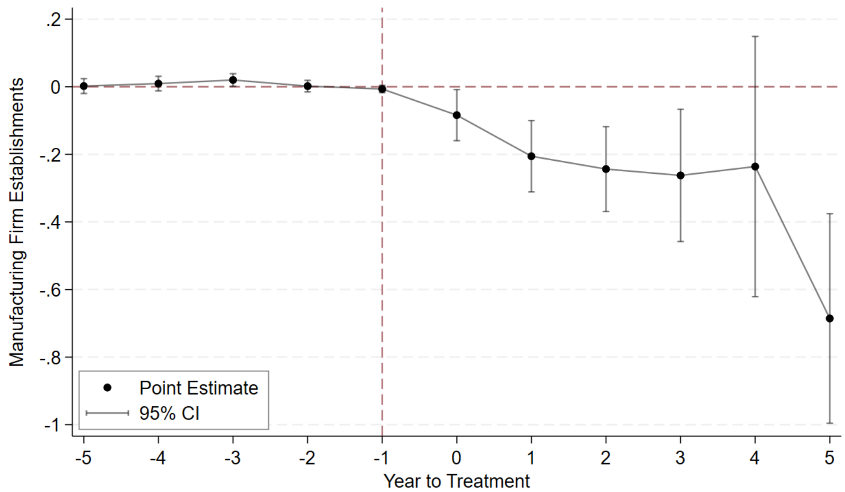


Figure 9: Dynamic Impact on Manufacturing Firm Establishment

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Manufacturing Firm Entry' refers to the total number of newly-established manufacturing enterprises; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the number of manufacturing firm establishment in treated municipalities is smaller than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

cost efficiencies through the displacement of labour by robots, likely further enhanced their competitive edge under the policy. If that is the case, then it would be harder for smaller firms to enter the market. This aligns with Table 7, where sectors like automobile and electrical, known for higher levels of robot penetration, also see greater reductions in new firm entries.

5.2 Improvements of Larger Manufacturing Firms

To further examine the disproportionate impact of policy implementation, I analyse firm counts, total assets, turnovers and employment figures for major industrial enterprises. As Table 8 illustrates, Column (1) shows that the effect of such a robot subsidy policy on the number of major industrial enterprise is negligible. However, I observe significant increases in total assets, turnovers and employment attributable to robot subsidy policies. Specifically, a 6.4% rise in total assets suggests enhanced asset investment by these larger firms after the introduction of such a policy, potentially reflecting an incentive for larger firms to invest in robots. Column (3) documents a 7.8% turnover increase following policy implementation, implying that these larger firms may have leveraged robots to boost productivity and, consequently, turnover. Employment also sees an increase of 5.8%, as shown in Column (4). This juxtaposition suggests that, while robot technology may replace some jobs, the resultant turnover and productivity gains could necessitate additional labour. Hence, the productivity benefits appear to outweigh the displacement effects of robots in the intensive margin. Despite the stable count of major industrial enterprises after the introduction of such a policy, their performance has improved. Particularly, given the decline in new entry for all manufacturing firms, I suggest that larger firms are the principal beneficiaries of such robot subsidy policies, and this has accentuated their initial advantages and increased the barriers for smaller firms entering the market.

Table 8: Aggregate ATT on Major Industrial Enterprises

(in IHS)	*Count* (1)	*Total Asset* (2)	*Turnover* (3)	*Employment* (4)
Demand Subsidy	0.015	0.064***	0.078**	0.058**
	(0.025)	(0.016)	(0.036)	(0.025)
N(obs)	2,820	2,680	2,800	2,350
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y

Note: (1) The results is based on SDID approach; (2) The coefficient is the ATT which averages the staggered treatment effect of all cohorts; (3) Outcome variables are in Inverse Hyperbolic Sine; (4) Standard errors are clustered at municipal level; (5) *, **, and *** respectively indicates 10%, 5%, and 1% significance level; (6) 'Count' refers to the total number of major industrial enterprises, 'Total Asset' refers to the value of total asset, 'Turnover' refers to the annual turnover and 'Employment' refers to the number of employees.

Total Assets

Figure 10 presents the dynamic impact of a robot subsidy policy on the total assets of major industrial enterprises in cities that adopt such a policy. Initially, prior to period 0, the differences in total assets between cities implementing such a policy and their synthetic counterparts are close to 0 and statistically insignificant. However, post period 0, I find a noticeable upward trajectory in total assets. The difference becomes statistically significant right after the introduction of robot subsidy, with treated cities exhibiting total assets over 4% greater than those in the control groups. This significant impact persists and intensifies over time, reaching 20% after the initial introduction of the subsidy. This highlights an increase in total investments by larger firms, starting three years after the introduction of a robot subsidy policy. Given that robot investments are categorized under total assets, it is plausible to attribute this trend to the acquisition of robots.

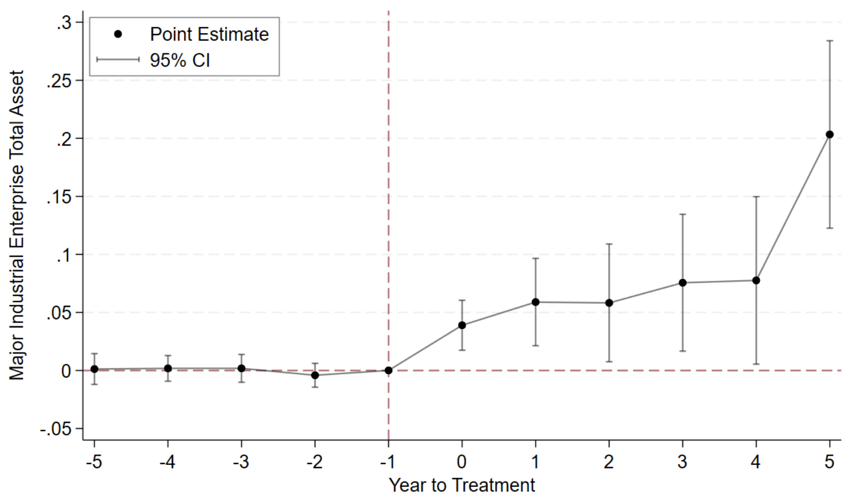


Figure 10: Dynamic Impact on Total Assets of Major Industrial Enterprises

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Major Industrial Enterprise Total Asset' refers to the municipal-level total assets of major industrial enterprises; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the total asset of major industrial firms in treated municipalities is larger than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

Annual Turnover

Figure 11 presents the dynamic impact of a robot subsidy policy on total revenue of major industrial enterprises in cities that implement such a policy. I observe an immediate and persistent effect on annual turnover after policy implementation. Mirroring the observations in Figure 10, I find no significant differences between cities implementing such a policy and their synthetic counterparts prior to period 0. Nonetheless, policy implementation results in an immediate effect in the treated cities, with a notable 5% increase in annual turnover observed in period 0 compared with the control groups. The intensity of this effect amplifies progressively, reaching approximately 30% by five years following the introduction of a robot subsidy policy.

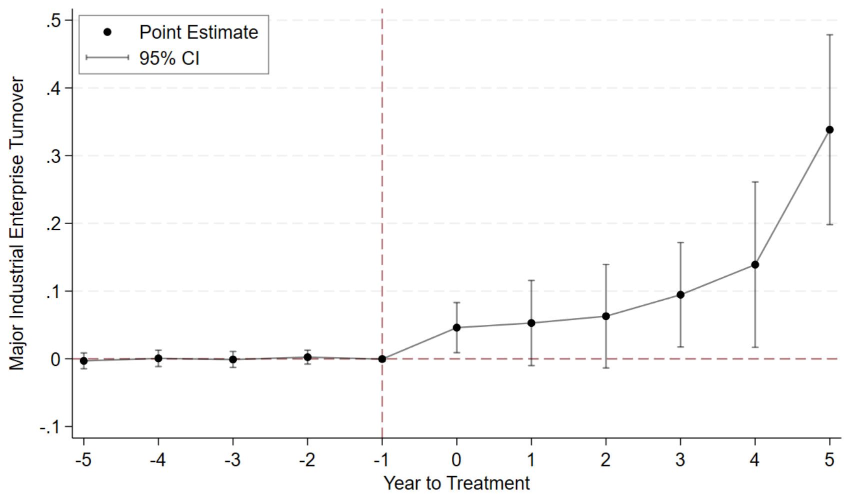


Figure 11: Dynamic Impact on Annual Turnover of Major Industrial Enterprises

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Major Industrial Enterprise Turnover' refers to the municipal-level annual turnover of major industrial enterprises; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the annual turnover of major industrial enterprises in treated municipalities is larger than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

Total Employment

Figure 11 presents the dynamic impact of a robot subsidy policy on total employment within major industrial enterprises in cities that adopt such a policy. An immediate and sustained effect on total employment is evident following policy implementation. Echoing the patterns observed in Figures 10 and 11, there is no notable disparity between the cities implementing such a policy and their synthetic counterparts prior to period 0. However, policy implementation results in a swift and persistent response in the treated cities, with total employment showing a significant increase compared with control groups from period 0 onwards. The effect increases from just under 1% in 2015 to approximately 20% by period 5, maintaining its significance throughout this period. This trend underscores the impact such policies can have on the substantial and lasting augmentation of employment levels in larger manufacturing enterprises.

This outcome appears counterintuitive at first glance, as the adoption of robots might result in reduced employment due to the potential for labour displacement. However, I attribute this phenomenon primarily to the productivity effect of robot adoption, rather than to the substitution effect. As depicted in Figure 11 and detailed in Table 8, there was a notable rise in turnover following policy implementation. This turnover surge is likely to spur an elevated demand for labour, culminating in the observed employment growth. Meanwhile, consistent with the implication of automation, the increase in employment is smaller in magnitude than the increases in total assets and turnover. The underlying dynamics of this counterintuitive result will be elaborated upon within my theoretical framework, offering a deeper exploration of the mechanisms at play.

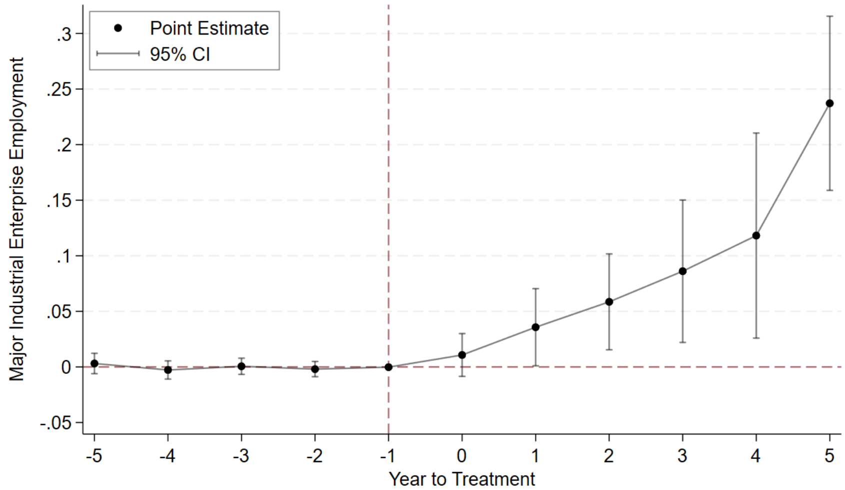


Figure 12: Dynamic Impact on Number of Employee of Major Industrial Enterprises

Note: (1) Each dot represents the policy effect estimated using SDID approach; (2) 'Major Industrial Enterprise Employment' refers to the municipal-level number of employees of major industrial enterprises; (3) Before period 0, the differences are not significant between the treated group and the synthetic control group; (4) Post period 0, a positive and significant estimate suggests that the number of employees of major industrial enterprises in treated municipalities is larger than that in control municipalities; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

5.3 Robustness Checks With Other DID Methods

Similar to the last section, I examine the robustness of the results by applying alternative DID methods to our analysis on the establishment of manufacturing firms and three metrics of financial performances of major industrial enterprises. Figures 13, 14, 15 and 16 present the results respectively.

Two key observations are described as followed. First, all three methods yield post-treatment effects that are consistent with those shown in Figures 9, 11, 10 and 12. This consistency suggests that my primary findings are robust across different methodological approaches and not solely dependent on the SDID method. Second, the traditional TWFE estimators indicate some significant differences between treated and control municipalities, particularly at period -5. This aligns with my OLS results, which suggest that the introduction of robot-subsidizing policies may be endogenous to observable factors such as fiscal capacity and the existing development of the robotics industry, as well as to unobservable factors. The methods proposed by De Chaisemartin and d'Haultfoeuille (2020) and Call-

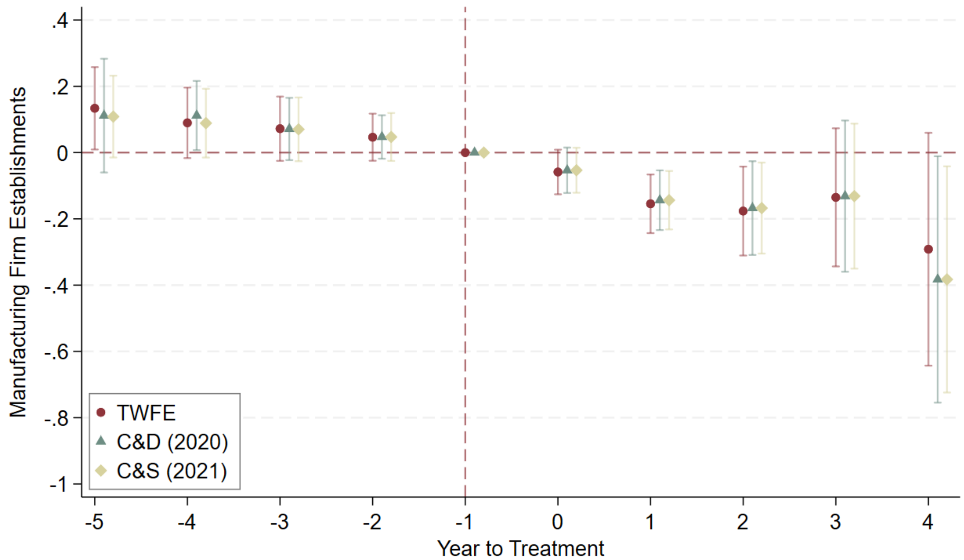


Figure 13: Event Study Robustness Check - Manufacturing Firm Establishments

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Manufacturing Firm Establishments' measures the IHS of municipal-level numbers of new manufacturing firm establishments between 2010 and 2019; (3) Before treatment, traditional TWFE shows slightly significant difference between treated and control municipalities in period -5, while C&D and C&S approaches help render the pre trend insignificant. That also supports the validity of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and negative estimates, suggesting the number of new manufacturing firm establishments in treated municipalities becomes persistently smaller than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

away and Sant'Anna (2021) effectively render the pre-treatment trends insignificant, thereby satisfying the parallel trends assumption necessary for valid DID identification. Nonetheless, the magnitude of the point estimates remains relatively large. These findings further validate the use of SDID as my primary identification strategy, as it mitigates significant pre-trends by constructing a credible synthetic counterfactual for treated municipalities using a comprehensive set of control units.

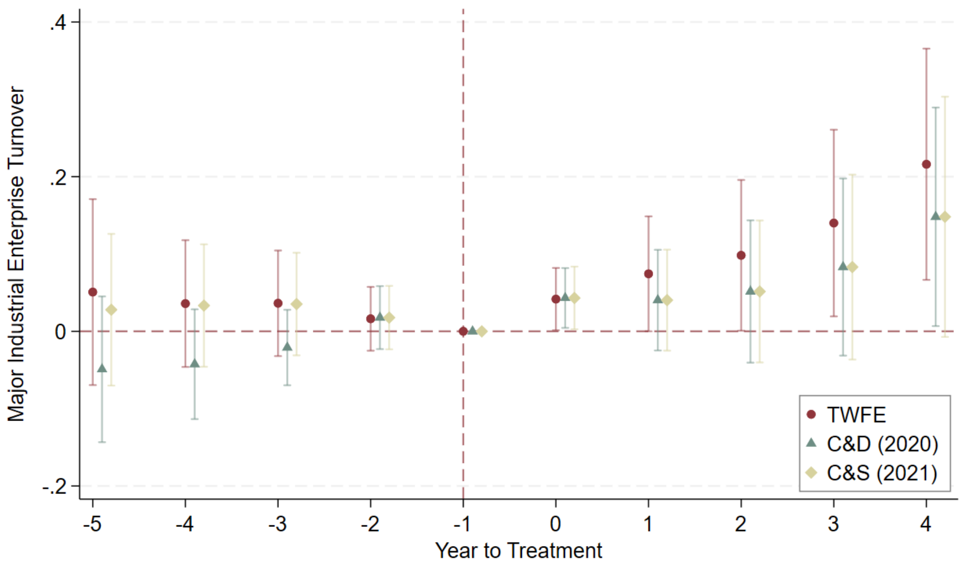


Figure 14: Event Study Robustness Check - Major Industrial Enterprise Turnover

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Major Industrial Enterprise Turnover' measures the IHS of municipal-level turnovers of major industrial enterprises (defined as firms with an annual turnover above 300 million USD) between 2011 and 2020; (3) Before treatment, neither of three methods shows significant difference between treated and control municipalities, while traditional TWFE shows slightly more positive point estimates. That also supports the validity of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and positive estimates, suggesting the major industrial enterprise turnover in treated municipalities becomes persistently larger than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

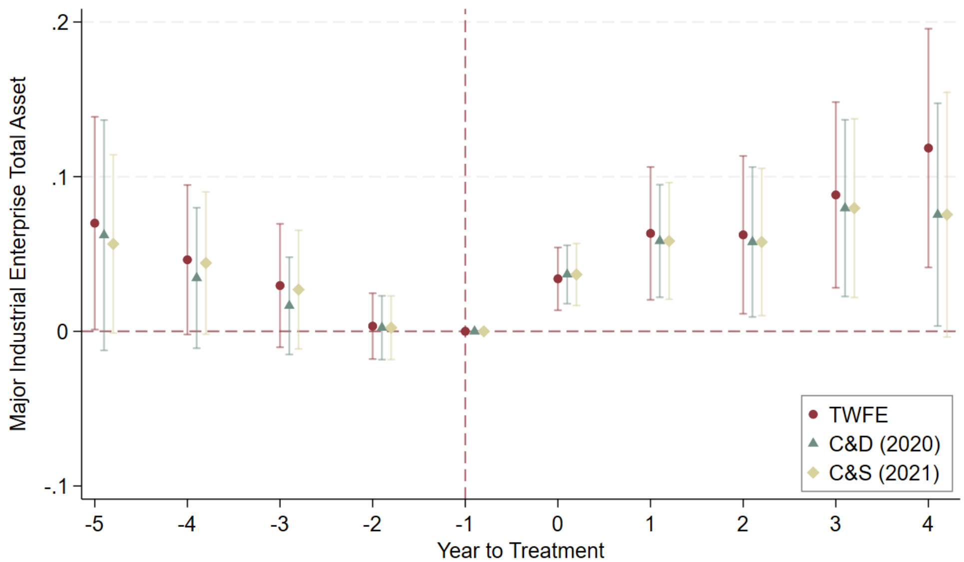


Figure 15: Event Study Robustness Check - Major Industrial Enterprise Total Asset

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Major Industrial Enterprise Total Asset' measures the IHS of municipal-level total assets of major industrial enterprises (defined as firms with an annual turnover above 300 million USD) between 2011 and 2020; (3) Before treatment, traditional TWFE shows slightly significant difference between treated and control municipalities in period -5, while C&D and C&S approaches help render the pre trend insignificant. All three methods yield relatively large point estimates, which strongly supports the use of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and positive estimates, suggesting the major industrial enterprise total assets in treated municipalities becomes persistently larger than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

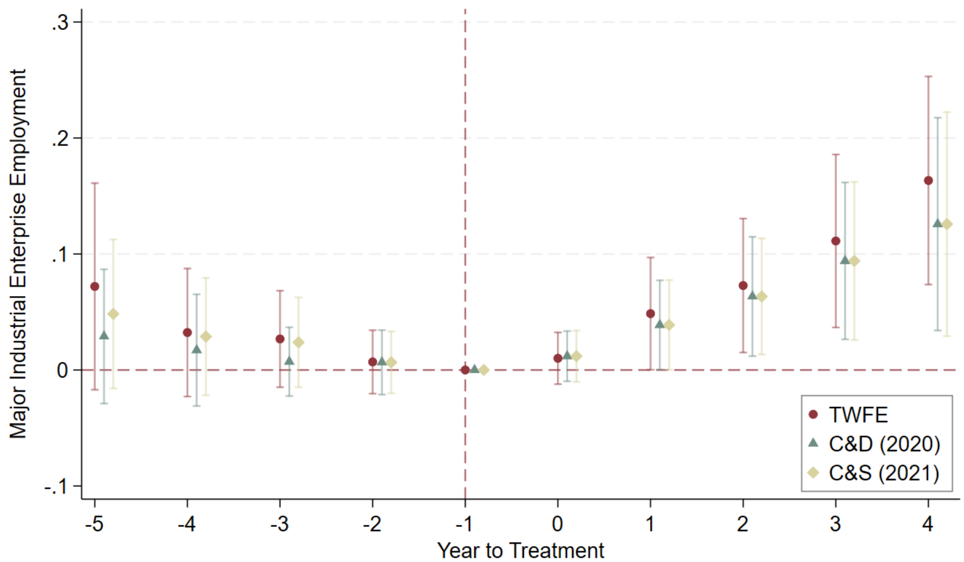


Figure 16: Event Study Robustness Check - Major Industrial Enterprise Employment

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach: 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D (2020)' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2020), 'C&S (2021)' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) 'Major Industrial Enterprise Employment' measures the IHS of municipal-level employments of major industrial enterprises (defined as firms with an annual turnover above 300 million USD) between 2011 and 2020; (3) Before treatment, neither of three methods shows significant difference between treated and control municipalities, while traditional TWFE shows slightly more positive point estimates. That also supports the validity of Synthetic DID in my setting; (4) Post treatment, all three methods yield significant and positive estimates, suggesting the major industrial enterprise employments in treated municipalities becomes persistently larger than that in control ones; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level. We report the confidence interval at 95% confidence level.

6 A Simple Model Exploring Distributional Impacts of Uniform Robot Subsidy

Before delving into the full model, I will first describe a simplified environment that incorporates exogenously-given borrowing costs (Hsieh and Klenow, 2009; Moll et al., 2017; David and Venkateswaran, 2019) with endogenous automation adoption (Acemoglu and Autor, 2012; Acemoglu and Restrepo, 2018) to illustrate how our model aligns with empirical findings. I will then discuss the impact of a uniform robot subsidy on automation dispersion and how the interplay affects overall productivity through static misallocation (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). My simple model abstracts from endogenous financial frictions as the microfoundation of the MPK wedges so as to shut down the dynamics of the misallocation itself. That has important quantitative implications but do not affect our qualitative arguments. In the full model I will introduce heterogeneous entrepreneurs so as to account for dynamic misallocation (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Gopinath et al., 2017; Da-Rocha et al., 2023) through through endogenous capital accumulation. By doing so I can quantify the efficiency implication of a uniform subsidy as well as disentangling the ensuing static and dynamics misallocation.

6.1 Environment

Households

There is a representative household that maximizes life-time utility subject to a flow budget constraint:

$$\begin{aligned} V(a_0) = \max_{\{c_t\}} \ & \int_0^\infty e^{-\varepsilon t} u(c_t) dt, \\ \text{s.t.} \quad & \dot{a}_t = r_t a_t + w_t + \pi_t - T_t - c_t, \end{aligned} \tag{1}$$

where r_t and w_t denote the interest rate and the wage, respectively, and π_t denotes profits from operating firms. T_t denotes the lump-sum tax that accounts the expenditure of the robot subsidy and the reimbursement from the MPK wedges. The detailed expression of T_t will be introduced later.

Final Good and Traditional Sector

There are two sectors in the economy: a traditional sector T and a modern sector M. The household consumes a single final good Y_t (which is also the numeraire) produced by combining the sectoral outputs $Y_{T,t}$ and $Y_{M,t}$ in a Cobb-Douglas manner with modern output share α:

$$Y_t = Y_{M,t}^{\alpha} Y_{T,t}^{1-\alpha}.$$

The traditional sector produces its sectoral output $Y_{T,t}$ using capital and labour through a Cobb-Douglas production technology, and supplies it in a perfectly competitive market:

$$\begin{aligned} \max_{\{Y_{T,t}, k_{T,t}, l_{T,t}\}} \quad & P_{T,t} Y_{T,t} - w_t l_{T,t} - r_t k_{T,t}, \\ \text{s.t.} \quad & Y_{T,t} = z_T k_{T,t}^{\beta} l_{T,t}^{1-\beta}. \end{aligned} \tag{2}$$

Modern Sector

There is a unit mass firms $i \in [0, 1]$ operating in the modern sector. The output of the modern sector, $Y_{M,t}$, is produced by aggregating the varieties supplied by firms, $Y_{i,t}$, using a CES production function with an elasticity of substitution $\sigma > 1$:

$$Y_{M,t} = \left[\int_0^1 y_{i,t}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}.$$

Hence, the demand for each variety y_i satisfies:

$$p_{i,t} = P_{M,t} Y_{M,t}^{\frac{1}{\sigma}} y_{i,t}^{-\frac{1}{\sigma}}.$$

Since the production side is static, I will omit the time subscript to maintain clarity in describing the firms' problem. Firms in the modern sector are characterized by three key components: endogenous automation adoption, exogenously-given MPK wedges, and a uniform robot subsidy.

Task-Based Framework To endogenize the adoption of industrial robots, I incorporate the task-based production technology as proposed by Acemoglu and Autor (2012) and Acemoglu and Restrepo (2018): In this framework, each variety y_i is produced through a continuum of tasks $j \in [0,1]$. For simplicity, I assume the absence of technological constraints, implying that all tasks are fully automatable. Consequently, capital and labour are considered perfect substitutes across these tasks:

$$y_{ij} = k_{ij} + \gamma(j) l_{ij}.$$

Here, $\gamma(j)$ represents the relative productivity of labour in performing task j, which is assumed to be strictly increasing in j. This assumption reflects the intuition that tasks indexed by higher j values are more complex, making them more efficiently produced by labour. Firms produce varieties using a CES production technology with elasticity ρ:

$$y_i = z_i \left[\int_0^1 y_{ij}^{\frac{\rho-1}{\rho}} dj \right]^{\frac{\rho}{\rho-1}}.$$

The optimization of the aforementioned equations determines a cutoff value, J_i, for task allocation. Intuitively, that implies that it is optimal for tasks indexed by $j \in [0, J_i]$ to be produced exclusively with capital, while tasks indexed by $j \in [J_i, 1]$ should be produced exclusively with labour. This allocation strategy results in the following production function:

$$y_i = z_i \left\{ J_i^{\frac{1}{\rho}} k_i^{\frac{\rho-1}{\rho}} + \left[\int_{J_i}^1 \gamma(x)^{\rho-1} dx \right]^{\frac{1}{\rho}} l_i^{\frac{\rho-1}{\rho}} \right\}^{\frac{\rho}{\rho-1}}.$$

Financial Frictions I assume the firms face financial frictions in the form of exogenously-given idiosyncratic borrowing costs, Φ_i (Hsieh and Klenow, 2009; Moll et al., 2017; David and Venkateswaran, 2019).[8] Since I think of Φ_i as a limit of capital usage instead of an actual expenditure, I model it in the form of a capital tax and will be paid back to the household as a lump-sum transfer. I further posit that $\Phi_i > 0$ and $Var(\Phi_i) > 0$, indicating that the financial frictions depress capital use in general and borrowing costs vary across firms.

In this toy model, I assume $\{\Phi_i\}_{i \in [0,1]}$ follows an exogenously-given distribution. I will endogenize it by connecting the borrow costs to the asset positions of heterogeneous en-

[8]While industrial enterprises in China face significant capital misallocation arising from multiple sources, I particularly concentrate on financial frictions, following evidence from prior research which indicates that such frictions constitute a significant determinant of idiosyncratic MPK wedges among manufacturing enterprises in China (Hsieh and Song, 2015; Wu, 2018; David and Venkateswaran, 2019).

trepreneurs in the full model.

Uniform Robot Subsidy As per the industrial robot subsidy policies enacted by Chinese municipalities, I model the policy intervention as a percentage subsidy, denoted by τ, applied to the capital rental rate r.

Optimization problem Firm i faces profit maximization problem formulated as follows:

$$\begin{aligned} \pi_i = \max_{\{y_i,k_i,l_i,J_i\}} \quad & p_i y_i - w l_i - (1-\tau) r k_i - \Phi_i k_i, \\ \text{s.t.} \quad & p_i = P_M Y_M^{\frac{1}{\sigma}} y_i^{-\frac{1}{\sigma}}, \\ & y_i = z_i \Big\{ J_i^{\frac{1}{\rho}} k_i^{\frac{\rho-1}{\rho}} + \Big[\int_{J_i}^1 \gamma(x)^{\rho-1} dx \Big]^{\frac{1}{\rho}} l_i^{\frac{\rho-1}{\rho}} \Big\}^{\frac{\rho}{\rho-1}}. \end{aligned} \tag{3}$$

Government Budget Constraint

The robot subsidy is financed by a lump-sum tax collected from the firms as well as by the idiosyncratic capital tax Φ_i. The government budget balance is given by equalizing the lump-sum tax T_t with the gap between robot subsidy expenditure and capital tax income:

$$\tau \int_0^1 k_{i,t} di = \int_0^1 \Phi_i k_{i,t} di + T_t. \tag{4}$$

Market Clearing Conditions

The wage rate w_t and interest rate r_t clear the labour and capital market respectively:

$$l_t^T + \int_0^1 l_{i,t} di = 1, \tag{5}$$

$$k_t^T + \int_0^1 k_{i,t} di = a_t. \tag{6}$$

Moreover, modern firms' prices $p_{i,t}$ aggregate to the sectoral price $p_{M,t}$ and the sectoral prices satistfy the one-price principle:

$$P_{M,t} = \Big[\int_0^1 p_{i,t}^{1-\sigma} di \Big]^{\frac{1}{1-\sigma}}, \tag{7}$$

$$1 = {\frac{P_{M,t}}{\alpha}}^{\alpha} {\frac{P_{T,t}}{1-\alpha}}^{1-\alpha}. \tag{8}$$

Equilibrium

The competitive equilibrium of the economy consists of household's consumption c_t and lump-sum tax T_t, traditional sector factor demands $k_{T,t}$ and $l_{T,t}$, modern firms' automation levels and factor demands $J_{i,t}$, $k_{i,t}$ and $l_{i,t}$, and prices w_t, r_t, $P_{i,t}$, $P_{M,t}$ and $P_{T,t}$ such that, given the distribution of borrowing costs $\{\Phi_i\}_{i\in[0,1]}$ and robot subsidy τ:

1. c_t satisfies the representative households's utility maximization problem (1);
2. $k_{T,t}$ and $l_{T,t}$ satisfy the traditional sector's profit maximization problem (2);
3. $J_{i,t}$, $k_{i,t}$ and $l_{i,t}$ satisfy mordern firms' profit maximization problem (3);
4. w_t and r_t satisfy the factor market clearing conditions (5) and (6), and $p_{i,t}$, $P_{M,t}$ and $P_{T,t}$ satisfy the one-price principle (7) and (8);
5. T_t satisfies the government budget balance condition (4).

6.2 Link to Empirical Findings

In this section, I explore the interaction between idiosyncratic borrowing costs and firms' decisions to automate and explain how this interplay helps to explain our empirical observations. As a brief introduction for the intuition, the idiosyncratic borrowing costs Φ_i cause dispersion of optimal automation levels J_i in the following way:

$$\gamma(J_i) = \frac{w}{(1-\tau)r + \Phi_i}.$$

Intuitively, the derived expression indicates the presence of borrowing costs, $\Phi_i > 0$, contribute to inefficiently low levels of automation adoption relative to the frictionless level. The degree of inefficiency varies among firms and intensifies as firm i encounters more severe limit of utilizing capital. Importantly, this variability in financial conditions also renders the effectiveness of a uniform automation subsidy, denoted by τ, to vary across firms:

$$\frac{\partial J_i}{\partial \tau} = \frac{\gamma(J_i)}{\gamma'(J_i)} \frac{r}{(1-\tau)r + \Phi_i}.$$

The above expression indicates that borrowing costs attenuate the response of the firm towards the subsidy: the greater the financial frictions faced by a firm, the less it will improve its automation in a robot subsidy. Intuitively, that is because the robot subsidy helps reduce the explicit capital cost r but does not facilitate access to capital captured by the implicit borrowing cost Φ_i. Therefore, if a firm is so financially-constrained that the implicit borrowing cost makes up the majority of its capital expenditure, then a robot subsidy alone will not make a significant change to its cost of adopting industrial robots. The following lemma elucidates how endogenous automation affects the marginal costs in response to an increase in the subsidy.

Lemma 1 *Given a rise of the uniform automation subsidy $\partial\tau$, the change of marginal cost, mc_i, faced by firm i is given by:*

$$\frac{\partial \log mc_i}{\partial \tau} = -\underbrace{\frac{J_i}{J_i + \gamma(J_i)^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}}_{\textit{Automation effect}}\underbrace{\frac{1}{(1-\tau)r+\Phi_i}}_{\textit{MPK wedge effect}},$$

$$\frac{\partial^2 \log mc_i}{\partial\tau\partial\Phi_i} > 0.$$

Lemma 1 suggests that an increase in the uniform subsidy τ consistently reduces marginal costs, yet its impact varies across firms. Specifically, firms with weaker borrowing constraints derive greater benefits from the subsidy. Regarding the mechanisms of dispersion, the productivity enhancements attributable to the subsidy can be decomposed into two distinct components. Intuitively, beyond the mechanical dispersion induced by existing MPK wedges, firms will also endogenously adjust their automation levels in response to the subsidy, thereby intensifying the dispersion in productivity gains. The subsequent proposition describes the equilibrium effects induced by a uniform automation subsidy.

Proposition 1 *Assume α is small enough, then there always exists a cutoff value for the MPK wedge, $\bar{\Phi}$, such that*

$$\left.\frac{\partial log(mc)}{\partial\tau}\right|_{\bar{\Phi}} = \int_0^1 \frac{\partial log(mc_i)}{\partial\tau}\cdot\frac{p_i y_i}{P_M Y_M}di.$$

And $\frac{\partial p_i y_i}{\partial\tau} > 0$ and $\frac{\partial\pi_i}{\partial\tau} > 0$ if and only if $\Phi_i < \bar{\Phi}$.

Proposition 1 shows how the benchmark framework helps to reconcile observed empirical outcomes.[9] Firms with greater access to capital ($\Phi_i < \bar{\Phi}$) disproportionately benefit from an increase in the uniform subsidy τ, enabling them to augment their turnovers and market shares at the expense of other competitors in the market. Conversely, firms constrained by tighter financial conditions ($\Phi_i > \bar{\Phi}$) are predisposed to suffer profit declines following the subsidy introduction. Assuming a constant fixed cost for ongoing business operations or endogenous occupation choice, this diminution in profits is likely to be translated in reduced entry of new firms.

6.3 Productivity and Efficiency Discussion

In this section, I explore the productivity and efficiency implications of a uniform robot subsidy in the presence of financial frictions and endogenous automation adoption. My analysis reveals that financial-friction-induced MPK wedges result in productivity and efficiency losses through two primary channels: a general suppression of capital usage and automation adoption, and the creation of automation dispersion across firms. With these two dimensions in mind, I demonstrate that a uniform robot subsidy affects overall efficiency via two distinct mechanisms: **enhancing mean automation** while simultaneously **intensifying automation dispersion**. These opposing dynamics indicate that the net efficiency impact of a uniform robot subsidy is highly contingent upon the specific nature of the prevailing financial frictions and the distribution of automation adoption among firms.

To make the analysis more mathematically tractable, I assume the elasticity of substitution between tasks $\rho = 1$, which reduces the production function to a Cobb-Douglas form:

$$y_i = z_i e^{\int_{J_i}^{1} \log \gamma(x) dx} (\frac{k_i}{J_i})^{J_i} (\frac{l_i}{1 - J_i})^{1-J_i}.$$

[9] Here I assume α is small enough so as to shut down the general equilibrium effects on factor prices and on final good demand. As will be shown in the full model, the main implications of our framework still hold given my calibration targeting the industrial sector in China.

Three Important Automation Measures

Before discussing the efficiency and productivity implications, I need to first introduce three important automation measures, namely individually-optimal automation levels $\{J_{i,t}\}_{i\in[0,1]}$, the socially-optimal automation level J_t^* and the dispersion-purged automation level $\bar{J}_t$. The set of individually-optimal automation levels $\{J_{i,t}\}_{i\in[0,1]}$ are the automation levels adopted in the decentralized economy defined in 6.1.

The socially-optimal automation level J_t^* is obtained from the social planner's problem of the economy, which is defined as followed:

Optimization 1 *(Social Planner's Problem)*

$$
\begin{aligned}
V^{SP}(a_0) = \max_{\{c_t, Y_{T,t}, Y_{M,t}, k_t^T, l_t^T, y_{i,t}, k_{i,t}, l_{i,t}, J_{i,t}\}} \quad & \int_0^\infty e^{-\epsilon t} u(c_t) dt, \\
s.t. \quad & \dot{a}_t = Y_{M,t}^{\alpha} Y_{T,t}^{1-\alpha} - c_t, \\
& Y_{T,t} = z_T k_{T,t}^{\beta} l_{T,t}^{1-\beta}, \\
& Y_{M,t} = \left[\int_0^1 y_{i,t}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \\
& y_{i,t} = z_i e^{\int_{J_{i,t}}^1 \log \gamma(x) dx} \left(\frac{k_{i,t}}{J_{i,t}}\right)^{J_{i,t}} \left(\frac{l_{i,t}}{1-J_{i,t}}\right)^{1-J_{i,t}}, \\
& k_t^T + \int_0^1 k_{i,t} di = a_t, \\
& l_t^T + \int_0^1 l_{i,t} di = 1.
\end{aligned}
$$

It can be demonstrated that the social planner's problem yields an identical level of automation for all firms. Intuitively, that is because the optimal level of automation depends solely on the factor prices, which are uniform across firms in the absence of idiosyncratic borrowing costs. I denote this uniform level of automation as J_t^* and refer to it as the socially optimal level, as it represents the efficient automation that all firms would adopt in the absence of distortions in factor usage. As will be demonstrated later, this level of automation maximizes the value function of the representative household.

Finally, I need to derive a measure of the mean automation level in the decentralized economy. This measure serves two key purposes: first, by comparing the mean automation level to the socially optimal level, I can assess the efficiency loss resulting from the uniform automation distortion experienced by all firms; second, by calculating the deviation of individually optimal automation levels from the mean level, I can evaluate the efficiency loss due to automation dispersion across firms.

To achieve this, I construct a hypothetical automation level, namely the dispersion-purged automation level $\bar{J}_t$, derived from the dispersion-purged problem defined as follows:

Optimization 2 *(Dispersion-Purged Problem)*

$$\begin{aligned}
\max_{\{y_{i,t},k_{i,t},l_{i,t},J_{i,t}\}} & \left[\int_0^1 y_{i,t}^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}}, \\
s.t. \quad & y_{i,t} = z_i e^{\int_{J_{i,t}}^1 \log\gamma(x)dx} (\frac{k_{i,t}}{J_{i,t}})^{J_{i,t}} (\frac{l_{i,t}}{1-J_{i,t}})^{1-J_{i,t}}, \\
& \int_0^1 k_{i,t} di = K_t^M, \\
& \int_0^1 l_{i,t} di = L_t^M,
\end{aligned}$$

where K_t^M and L_t^M denote the modern sector capital and labour demands in the decentralized economy. By solving Optimization (2) we obtain a simple equation that determines the dispersion-purged automation level $\bar{J}_t$:

$$\frac{\bar{J}_t}{1-\bar{J}_t}\gamma(\bar{J}_t) = \frac{K_t^M}{L_t^M}.$$

The dispersion-purged problem aims to maximize the modern sector's output given the aggregate factor demands in the decentralized equilibrium, assuming unrestricted resource allocation across firms. By aligning the aggregate factor demands with the decentralized inputs, K_t^M and L_t^M, I preserve the distortions in aggregate factor demand resulting from mean automation depression (the gap between mean automation and the socially optimal level). Conversely, the absence of restrictions on factor allocation across firms ensures that all firms face identical shadow prices for factors. This setting effectively neutralizes the effects of heterogeneity in production technologies captured by automation dispersion (the deviation of individually optimal automation from the mean level).

Decomposing the Efficiency Impact of a Uniform Robot Subsidy

With these three automation levels in hand, I now consider how a marginal increase in a uniform robot subsidy τ affects the value function of the representative household $V(a_t; \{\Phi_i\}, \tau)$ given existing MPK wedges $\{\Phi_i\}$. We first focus on how a rise of the subsidy affects static incomes:

Proposition 2 *Assume α is small enough, then the period-by-period net income change due to a marginal rise of the uniform robot subsidy τ can be described by:*

$$\frac{\partial \pi_t}{\partial \tau} - \frac{\partial T_t}{\partial \tau} = \frac{\sigma - 1}{\sigma}\alpha y_t \Bigg\{ \underbrace{\frac{\partial log(P_{M,t})}{\partial \tau}}_{\textit{Monopoly Power}} + \underbrace{\int_0^1 r_t(\bar{\Phi} - \tau)\left(\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial \bar{k}_{i,t}}{\partial \tau}\right) di}_{\textit{Second-Order Term}}$$
$$+ \underbrace{\left[\gamma(\bar{J}_t)^{-1} - \gamma(J_t^*)^{-1}\right] \frac{\partial}{\partial \tau}\left[\nu(\bar{J}_t)\right]}_{\textit{Mean Automation}} + \underbrace{\int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \frac{\partial}{\partial \tau}\left[\nu(J_{i,t}) \cdot \frac{p_{i,t} y_{i,t}}{P_{M,t} Y_{M,t}}\right] di}_{\textit{Automation Dispersion}} \Bigg\},$$

where $\gamma(j)$ represents the comparative productivity of labour in performing task j and $\nu(j) = j \cdot \gamma(j)$ is an increasing function in j.

I again shut down the general equilibrium effects by assuming α is sufficiently small. Proposition 2 demonstrates that a marginal increase in the robot subsidy affects the household's period-by-period budget constraint by enhancing the profits of the modern sector but increasing the tax burden.

The net effect can be decomposed into four components: the first component represents the typical distortion arising from a monopolistically competitive setting, while the second component is a second-order term. Of greater interest are the remaining two terms, which pertain to mean automation and automation dispersion. The mean automation term captures the net income change arising from the deviation of dispersion-purged automation $\bar{J}_t$ from the socially optimal level, J_t^*. Given that $\gamma(\cdot)$ is an increasing function, the mean automation term becomes positive if and only if the mean automation of the economy is below the socially optimal level, i.e., $\bar{J}_t < J_t^*$. In the context of the industrial sector in China, where financial frictions are a significant determinant of MPK wedges ($\Phi_i > 0$ for $\forall i$), firms' automation adoption is likely depressed, and the economy tends to benefit from a positive mean automation effect.

The automation dispersion term captures the net income loss resulting from the deviation of individually optimal automation levels $\{J_i\}_{i\in[0,1]}$ from the dispersion-purged automation, $\bar{J}_t$. This component is always negative. Intuitively, firms with high (low) automation levels $J_{i,t}$ tend to have negative (positive) deviations from the mean $\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}$. As shown in the previous subsection, firms with high (low) automation also tend to increase (decrease) their market shares $\frac{p_{i,t}y_{i,t}}{P_{M,t}Y_{M,t}}$ and gain more (less) improvements in automation $\nu(J_{i,t})$ with a uniform subsidy. Thus, the automation dispersion term is biased toward firms with negative deviations, implying that a robot subsidy can deteriorate the household's budget constraint by exacerbating automation dispersion across firms.

The following proposition connects the period-by-period income change to the value function of the representative household and summarizes the main efficiency implication:

Proposition 3 *A marginal rise of the uniform robot subsidy affects the value function of the household in the follow way:*

$$\frac{\partial V(a_t;\{\Phi_i\},\tau)}{\partial \tau} = \int_t^{\infty} e^{-\epsilon(s-t)}\lambda_t\left(\frac{\partial \pi_t}{\partial \tau} - \frac{\partial T_t}{\partial \tau}\right)ds,$$

where λ_t represents the stochastic discount factor at time t and $\frac{\partial \pi_t}{\partial \tau} - \frac{\partial T_t}{\partial \tau}$ measures the period-by-period net income change described in Proposition 2.

Propositions 2 and 3 underscore a key takeaway from this analysis: while a uniform robot subsidy can help correct aggregate factor demand distortions in China's industrial sector (**improving mean automation efficiency**), it does so at the cost of exacerbating the dispersion of technology usage across firms (**intensifying automation dispersion**). The underlying rationale is as follows: On the one hand, pre-existing financial frictions inherently depress the economy's incentive to adopt automation, leading to efficiency loss. When the subsidy τ is modest, it boosts firms' automation adoption and realigns aggregate factor usage to efficient levels. Hence, the mean automation term is strictly positive, and the household's value function could increase with the subsidy τ.

On the other hand, financial frictions introduce ex-ante distortions in factor allocation across firms. As discussed in the last subsection, the presence of idiosyncratic borrowing cost causes firms to adopt different levels of automation before the subsidy and thus derive varying benefits from such a policy. This differential impact is further intensified by ex-post endogenous automation adoption, as detailed in the next subsection. Thus, Propositions 2 and 3 demonstrate that an increase in τ unambiguously exacerbates the efficiency loss induced by automation dispersion.

Propositions 2 and 3 show that for a uniform robot subsidy to enhance overall efficiency, it must be designed to balance these two countervailing forces. The magnitudes of both types of inefficiencies are influenced by the distribution of financial frictions. Therefore, the design of the subsidy should be tailored to the characteristics of Φ_i. As will be illustrated in the full model, my calibration shows a subsidy between 10 to 20% could achieve the greatest improvement in social welfare.

How Automation Dispersion Amplifies Productivity Loss

To further explore the efficiency losses attributable to automation dispersion and to illustrate how endogenous automation could amplify productivity losses caused by capital misallocation (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008), I analyze the productivity gap between the decentralized equilibrium and the dispersion-purged equilibrium as defined in Optimization 2. While both equilibria are subject to identical mean automation depression as they generate identical aggregate factor demands, the dispersion-purged equilibrium eliminates the effects of automation dispersion. Intuitively, Optimization 2 elucidates the potential output of the modern sector using the decentralized equilibrium's factor inputs, under the assumption of an absence of capital misallocation across firms. Consequently, the disparity between these two frameworks exclusively reflects the effects of automation dispersion and idiosyncratic borrowing costs.

The subsequent corollary describes the aggregate production functions derived from the decentralized equilibrium and dispersion-purged equilibrium respectively. To keep the notations clear I neglect the time subscript:

Lemma 2 *Assume $\gamma(x) = \exp(Ax)$ and denote $\Delta J_i = J_i - \bar{J}$. The modern sector output*

y^M derived from the decentralized equilibrium can be expressed by:

$$y^M = TFP \cdot \left(\int_0^1 z_i^{\sigma-1} di\right)^{\frac{1}{\sigma-1}} e^{\frac{A}{2}(1-\bar{J}^2)} (\frac{K^M}{\bar{J}})^{\bar{J}} (\frac{L^M}{1-\bar{J}})^{1-\bar{J}}.$$

Given the same aggregate factor inputs K^M and L^M, the aggregate production function derived from dispersion-purged equilibrium is described by:

$$y^M = \left(\int_0^1 z_i^{\sigma-1} di\right)^{\frac{1}{\sigma-1}} e^{\frac{A}{2}(1-\bar{J}^2)} (\frac{K^M}{\bar{J}})^{\bar{J}} (\frac{L^M}{1-\bar{J}})^{1-\bar{J}}.$$

Hence the productivity loss from capital misallocation in the presence of endogenous automation can be captured by the TFP term:

$$TFP_{EA} = \left(\int_0^1 z_i^{\sigma-1} di\right)^{-\frac{1}{\sigma-1}} \frac{\left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)} e^{\frac{A}{2}(\sigma-1)\Delta J_i{}^2} di\right]^{\frac{\sigma}{\sigma-1}}}{\left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)-1} e^{\frac{A}{2}(\sigma-1)\Delta J_i{}^2} \frac{J_i}{\bar{J}} di\right]^{\bar{J}} \left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)} e^{\frac{A}{2}(\sigma-1)\Delta J_i{}^2} \frac{1-J_i}{1-\bar{J}} di\right]^{1-\bar{J}}},$$

where $\mu_i = (1-\tau)r + \Phi_i$ and $\bar{\mu} = \frac{w}{r}\gamma(\bar{J})^{-1}$.

Lemma 2 describes the dispersion inefficiency in the form of TFP reduction. One can easily show that if there is no MPK wedge dispersion $\mu_i \equiv \bar{\mu}$, then $TFP = 1$ and the decentralized equilibrium is as efficient as the dispersion-purged equilibrium.

I now proceed to analyzing how automation intensifies the productivity loss. The components highlighted in red within the TFP expression represent the influences attributed to endogenous automation adoption. By setting $\Delta J_i = 0$, I shut down the endogenous automation adoption and assume that all firms adhere to a uniform automation level $\bar{J}$. The ensuing expression details the TFP with no endogenous automation, which I denote as Hsieh and Klenow (HK) productivity loss introduced in their 2009 work:

$$TFP_{\text{HK}} = \left(\int_0^1 z_i^{\sigma-1} di\right)^{-\frac{1}{\sigma-1}} \frac{\left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)} di\right]^{\frac{\sigma}{\sigma-1}}}{\left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)-1} di\right]^{\bar{J}} \left[\int_0^1 z_i^{\sigma-1} \left(\frac{\mu_i}{\bar{\mu}}\right)^{-\bar{J}(\sigma-1)} di\right]^{1-\bar{J}}}.$$

To see more clearly how it differs from the productivity loss with endogenous automation, I further assume the dispersion of MPK wedges $\{\frac{\mu_i}{\bar{\mu}}\}$ follows a lognormal distribution $\log(\frac{\mu_i}{\bar{\mu}}) \sim N(0, V)$. The HK productivity loss can be approximated by:

$$\log(TFP_{HK}) \propto -\frac{1}{2}[\bar{J}(\sigma-1)+1]\bar{J}V,$$

which is consistent with the result obtained in Hsieh and Klenow (2009) and shows that the TFP reduces as the variance of MPK wedges increases. The following proposition shows the closed-form approximation of the dispersion inefficiency with endogenous automation.

Proposition 4 *Assume* $\log(\frac{\mu_i}{\bar{\mu}}) \sim N(0, V)$. *When* V *is small enough, the dispersion inefficiency with endogenous automation can be approximated by:*

$$\log(TFP) \propto \underbrace{f(V) \cdot \log(TFP_{HK})}_{\textit{Amplification}} - \underbrace{\left[A + \frac{1}{2\bar{J}(1-\bar{J})}\right] f(V) \cdot V}_{\textit{Excessive Factor Demand}} + \underbrace{\frac{1}{2(\sigma-1)}\log[f(V)]}_{\textit{Individual Productivity Gain}}.$$

where $f(V) = [1 - A(\sigma-1)V]^{-1} > 1$.

Proposition 4 shows the impacts of MPK wedges variance V on the total factor productivity $\log(TFP)$ can be decomposed into three parts. The intuitions are as followed.

Amplification The initial term demonstrates that endogenous automation directly exacerbates the productivity loss induced by conventional MPK dispersion. This occurs because firms encountering high (or low) MPK wedges will proactively decrease (or increase) their automation levels, diverging from the dispersion-purged automation level $\bar{J}$. Since $\bar{J}$ is optimal under constrained aggregate factor inputs, such deviations negatively impact overall TFP, thereby intensifying the conventional MPK dispersion productivity loss, captured by $\log(TFP_{HK})$. In terms of magnitude, $f(V)$ exceeds one and increases in V, indicating that greater dispersion in MPK wedges contributes to greater dispersion in automation levels, which in turn intensifies the amplification effect.

Excessive Factor Demand The second term illustrates that endogenous automation reduces overall productivity by prompting excessive factor demands. Intuitively, as firms facing high (or low) MPK wedges proactively adjust their automation levels, they consequently increase their utilization of capital (or labour) disproportionately. Collectively, this behavior results in aggregate factor demands that exceed those under the dispersion-purged automation level $\bar{J}$, thereby eroding TFP. As detailed in Proposition 4, this effect of excessive factor demand escalates with the variance of MPK wedges V. Consequently, the greater the dispersion in MPK wedges, the more pronounced the excessive factor demands and the resultant efficiency loss becomes.

Individual Productivity Gain The final term illustrates that endogenous automation can potentially enhance overall productivity by boosting individual firms' productivity, counteracting the negative effects of the previous mechanisms. Intuitively, allowing firms to tailor their production functions in response to effective factor prices enhances their individual productivity, which subsequently contributes to an increase in aggregate TFP. As described in Proposition 4, this mechanism operates in contrast to the other two channels and intensifies with the variance of MPK wedges V. The greater the dispersion of MPK wedges, the more significant are the benefits that individual firms derive from the flexibility to adjust their production functions.

To visualize the magnitudes of the dispersion inefficiency and three channels, I conduct a numerical practice with parameter values $A = 2$, $\sigma = 5$ and $J = 0.33$. Figure 17 shows the dispersion inefficiency without endogenous automation and decomposition of dispersion inefficiency with endogenous automation. As posited by Hsieh and Klenow (2009), dispersion in MPK wedges results in an aggregate TFP below one, signifying a loss in overall efficiency. When accounting for endogenous automation, two competing effects emerge: the amplification and excessive factor demand effects further depress TFP, while the productivity gain effect acts to alleviate this inefficiency.

Figure 18 illustrates the cumulative impact of endogenous automation. The amplification effect and the excessive factor demand effect unambiguously outweigh the productivity gain effect, which results in the overall TFP falling below the level without automation. This implies that endogenous automation indeed exacerbates the inefficiency arising from MPK wedge dispersion.

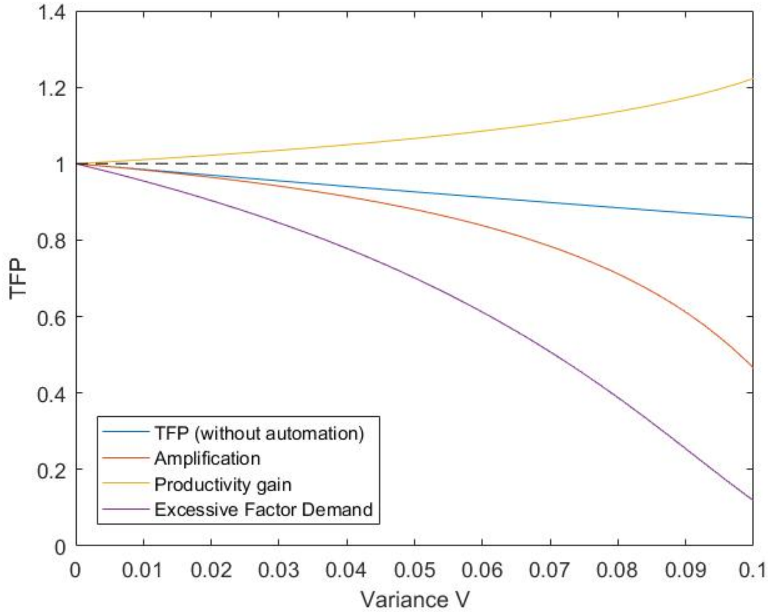


Figure 17: TFP Without Automation and Decomposition of TFP With Automation

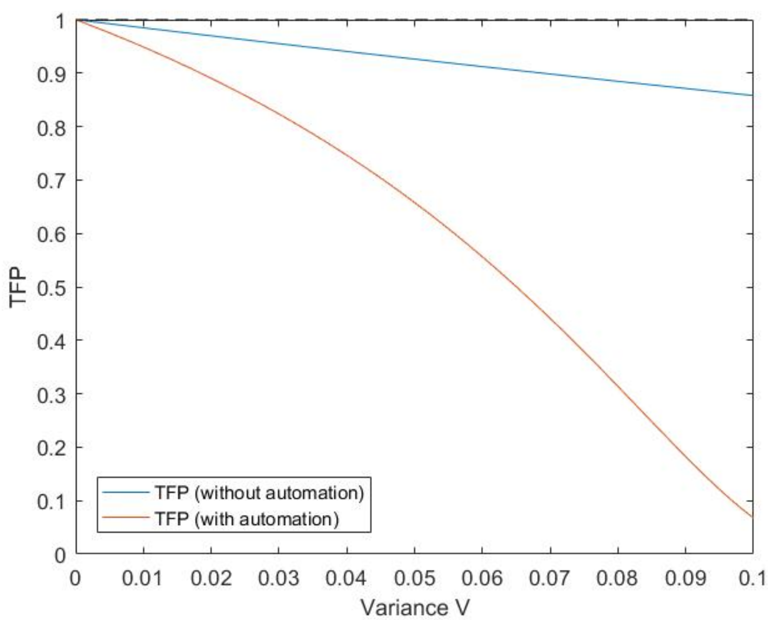


Figure 18: TFP Without Automation and TFP With Automation

7 Full Model Quantifying Efficiency Implications of Uniform Robot Subsidy

In the full model, I will integrate the static misallocation described in the last section into a dynamic environment by connecting idiosyncratic borrowing costs to asset positions of heterogeneous entrepreneurs. Different from mainstream studies in dynamic misallocation which focus on productivity-enhancing investments of firms (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Gopinath et al., 2017; Da-Rocha et al., 2023), I argue the adoption of industrial robots could affect labour and capital income disproportionally, rendering exacerbated capital accumulation dispersion and subsequent enlarged efficiency loss from inequality (e.g., Moll et al. (2022)).

7.1 Environment

Households

There is a unit mass of households $i \in [0, 1]$ that differ in their managerial talents $z_{i,t}$. Households maximize their discounted utility from consumption subject to a flow budget constraint and occupation choice:

$$\begin{aligned} V(a_{i,0}, z_{i,t}) = \max_{\{c_{i,t}\}} & \int_0^\infty e^{-\varepsilon t} \log(c_{i,t}) dt, \\ \text{s.t.} \quad & \dot{a_{i,t}} = r_t a_{i,t} + \max\{w_t, \pi_{i,t} - c_f\} - T_t^H - c_{i,t}. \end{aligned} \tag{9}$$

Households can flexibly choose to work as workers and earn the wage income w_t, or work as entrepreneurs and earn the profit income after deducing fixed operation cost $\pi_{i,t} - c_f$. The profit income $\pi_{i,t}$ is a function of the asset position of the entrepreneur $a_{i,t}$ and its entrepreneurial talent $z_{i,t}$. I will describe the detailed expression of the profit function and the stochastic process of the entrepreneurial talent later.

I further assume that the capital accumulation is subject to dissipation shocks that arrive at a Poisson rate p. Following Moll et al. (2022), I assume that if household i receives the dissipation shock, then it immediately eats all of its wealth and is left with zero asset position, thus $a_{i,t} = 0$.[10] This setting renders the actual discount rate of the households, ε, to be equal to the sum of actual discount rate and the arrival rate of the dissipation shock.

The Hamilton-Jacob-Bellman equation of the household's problem is given by:

$$\begin{aligned} \epsilon V(a_{i,t}, z_{i,t}) = \max_{\{c_{i,t}\}} \ & \log(c_{i,t}) + \frac{\partial V_{i,t}}{\partial a_{i,t}} \left[r_t a_{i,t} + \max\{w_t, \pi_{i,t} - c_f\} - T_t^H - c_{i,t} \right] \\ & + \frac{\partial V_{i,t}}{\partial z_{i,t}} \mu(z_{i,t}) + \frac{1}{2} \frac{\partial^2 V_{i,t}}{\partial z_{i,t}^2} \sigma(z_{i,t})^2. \end{aligned} \tag{10}$$

Equation (10) solves the optimal saving function $s(a, z)$. Define the stationary PDF of the households as $g(a, z)$, then it satisfies the following Kolmogorov Forward equation:

$$0 = -\frac{\partial}{\partial a} \big[s(a, z) g(a, z) \big] - \frac{\partial}{\partial z} [\mu(z) g(a, z)] + \frac{1}{2} \frac{\partial^2}{\partial z^2} [\sigma(z)^2 g(a, z)] - p g(a, z) + p \psi(a, z). \tag{11}$$

Here, $\psi(a, z)$ denotes the entry distribution after the dissipation shock realizes so that $\psi(a, z) = 0$ for any $a > 0$.

Firms

Denote the set of households that choose to be entrepreneurs as Ω_t. Each entrepreneur i produces its variety $y_{i,t}$ with labour $l_{i,t}$, capital $k_{i,t}$ and industrial robots $m_{i,t}$. The varieties aggregate to a single final good y_t in a CES way with elasticity $\sigma > 1$:

$$y_t = \left[\int_{i \in \Omega_t} y_{i,t}^{\frac{\sigma - 1}{\sigma}} di \right]^{\frac{\sigma}{\sigma - 1}}.$$

As introduced in Section 6, entrepreneur i maximizes the profit π_i subject to endogenous automation adoption and financial frictions. The dynamic framework departs from the simplified production technology in two ways: First, I endogenize the financial frictions by connecting the borrowing cost per unit of capital expenditure Φ_i to the asset positions of the household. I adopt the functional form proposed by David and Venkateswaran (2019):

$$\Phi(a_{i,t}) = \beta a_{i,t}^{\omega},$$

[10]Introducing the dissipation shock provides a stabilizing force to ensure the existence of stationary distribution of wealth, see e.g., Gabaix et al. (2016); Moll et al. (2022).

where β captures the overall magnitude of financial frictions and $\omega < 0$ captures the elasticity of the borrowing constraints to the entrepreneurs' asset positions. Moreover, I assume traditional capital and industrial robots are affected by identical borrowing costs.

Second, I explicitly distinguish industrial robots $m_{i,t}$ from traditional capital $k_{i,t}$. More specifically, each firm produces its variety through a unit mass of tasks $j \in [0, 1]$ with CES elasticity ρ:

$$y_{i,t} = z_i \left[\int_0^1 y_{ij,t}^{\frac{\rho-1}{\rho}} dj \right]^{\frac{\rho}{\rho-1}}.$$

Task outputs $y_{ij,t}$ are produced with industrial robots $m_{ij,t}$ and the so-called capital service $kl_{ij,t}$ that represents the combination of traditional capital and labour inputs: $kl_{ij,t} = k_{ij,t}^{\alpha} l_{ij,t}^{1-\alpha}$. Capital service and industrial robots are considered perfect substitutes across tasks:

$$y_{ij,t} = m_{ij,t} + \gamma(j) kl_{ij,t},$$

where $\gamma(j)$ represents the comparative productivity of capital service to industrial robots in performing task j. The optimization of the aforementioned equations yields an optimal cutoff value for task allocation J_i such that tasks $j \in [0, J_i]$ are performed exclusively by industrial robots and tasks $j \in [J_i, 1]$ are performed exclusively by capital service. Together with the financial frictions setup, this allocation strategy results in the following profit maximization problem:

$$\begin{aligned} \pi_{i,t} = \max_{\{y_{i,t}, k_{i,t}, l_{i,t}, m_{i,t}, J_{i,t}\}} \quad & p_{i,t} y_{i,t} - w_t l_{i,t} - [(1 + \Phi(a_{i,t})) r_t + \delta] k_{i,t} - [(1 + \Phi(a_{i,t}) - \tau_t) r_t^m + \delta] m_{i,t} + T_{i,t}^F, \\ s.t. \quad & p_{i,t} = y_t^{\frac{1}{\sigma}} {y_{i,t}}^{-\frac{1}{\sigma}}, \\ & kl_{i,t} = k_{i,t}^{\alpha} l_{i,t}^{1-\alpha}, \\ & y_{i,t} = z_i \left\{ {J_{i,t}}^{\frac{1}{\rho}} m_{i,t}^{\frac{\rho-1}{\rho}} + \left[\int_{J_{i,t}}^1 \gamma(x)^{\rho-1} dx \right]^{\frac{1}{\rho}} kl_{i,t}^{\frac{\rho-1}{\rho}} \right\}^{\frac{\rho}{\rho-1}}, \end{aligned} \tag{12}$$

with $T_{i,t}^F = \Phi(a_{i,t})[r_t k_{i,t} + r_t^m m_{i,t}]$.[11] and $z_{i,t}$ denotes the entrepreneur's managerial talent.

[11] As mentioned in Section 6, the lump-sum transfer $T_{i,t}^F$ captures the idea that, although the financial frictions enter the problem in the form of an extra borrowing cost, it does not incur a direct profit reduction to the entrepreneur but rather act purely as a restriction of utilizing capital and industrial robots.

The logarithm of entrepreneurial talent follows an Ornstein-Uhlenbeck process described by:

$$d\log(z_{i,t}) = \theta_z[\mu_z - log(z_{i,t})]dt + \sigma_z dW_{i,t}.$$

Here, $\theta_z > 0$ measures the autocorrelation of the process and μ_z and σ_z characterize the mean and variance of the stationary distribution of $z_{i,t}$. $dW_{i,t}$ denotes the Wiener process. The process yields a stationary distribution for managerial talent $\log(z_{i,t}) \sim N(\mu_z, \frac{\sigma_z^2}{2\theta_z})$. Hereby, we denote $\mu(z_{i,t}) = \theta_z[\mu_z - \log(z_{i,t})]z_{i,t} + \frac{\sigma_z^2}{2}z_{i,t}$ and $\sigma(z_{i,t}) = \sigma_z z_{i,t}$. The stochastic process of $z_{i,t}$ can be rewritten as:

$$dz_{i,t} = \mu(z_{i,t})dt + \sigma(z_{i,t})dW_{i,t}.$$

A special case of Equation 12 is when $J_i = 0$ and the production function is reduced to a standard Cobb-Douglas form with capital share α. That corresponds to the scenario where the firm utilizes no industrial robot in its production and relies total on the traditional technology. In the calibration I will rely on this special case to distinguish parameters governing the tradition and automation technologies.

Government Budget Constraint

The government finances the robot subsidy τ_t with a lump-sum tax collected from the households T_t^H. The government satisfies a period-by-period budget constraint as followed:

$$T_t^H = \tau_t r_t^m \int_{i\in\Omega_t} m_{i,t} di. \tag{13}$$

Market Clearing

There is a robotics industry where traditional capital k_t can be converted into industrial robots m_t with productivity z_t^m. Wage rate w_t and interest rate r_t clear the labour and capital market respectively:

$$\int_{i\in\Omega_t} l_{i,t} di = 1 - |\Omega_t|, \tag{14}$$

$$\int_{i\in\Omega_t} k_{i,t} di + \int_{i\in\Omega_t} \frac{m_{i,t}}{z_t^m} di = \int_0^1 a_{i,t} di. \tag{15}$$

Moreover, the prices of varieties $\{p_{i,t}\}_{i\in\Omega_t}$ satisfy the one-price principle:

$$\left[\int_{i\in\Omega_t} p_{i,t}^{1-\sigma} di\right]^{\frac{1}{1-\sigma}} = 1. \tag{16}$$

Equilibrium

The stationary equilibrium consists of a stationary distribution of the households $g(a, z)$, households' consumption and occupational choices $c(a, z)$ and Ω, firms' automation levels and factor demands $J(a, z)$, $k(a, z)$, $l(a, z)$ and $m(a, z)$, the government's lump-sum tax T^H, and prices w, r, $p(a, z)$ such that, given a uniform robot subsidy τ:

1. $c(a, z)$ and Ω satisfy the households' HJB equation (10);
2. $J(a, z)$, $k(a, z)$, $l(a, z)$ and $m(a, z)$ satisfy the firms' profit maximization problem (12);
3. w and r satisfy the factor market clearing conditions (14) and (15), and $p(a, z)$ satisfies the one-price principle (16);
4. T^H satisfies the government budget balance condition (13);
5. $g(a, z)$ satisfies the Kolmogorov Forward equation (11);

7.2 Calibration

My benchmark model is calibrated to match the productivity dispersion, financial frictions, and industrial robot density of China's industrial sector in 2010. I then calibrate the task-based technology to reflect the growth of industrial robot stock between 2010 and 2013, a period prior to the introduction of the first municipal-level robot subsidy in 2014. Therefore, the growth in industrial robot usage during this period can be attributed solely to changes in robot prices. Table 9 presents the calibration targets.

For households preferences, I adopt a standard value for the elasticity of substitution across varieties $\sigma = 7$. I calibrate the yearly discount rate ϵ to match a capital-to-output ratio of 3 in 2010. Following seminal works of Moll et al. (2022); Jakobsen et al. (2020); Brülhart et al. (2022), I set the yearly dissipation rate, p, to achieve a capital supply elasticity

$dlog(K)/dr \approx 25$.

Turning to the production technology, I set the labour input elasticity in producing capital service $\alpha = 0.6$ to match China's 2010 labour income share when industrial robot usage was minimal. I adopt a standard value for capital depreciation rate, $\delta = 0.05$, and for the span-of-control parameter, $\nu = 0.85$ [12]. The fixed cost of operation, c_f, is calibrated to generate an average employment of 58.15 workers per firm, aligning with the average firm size in China's manufacturing sector in 2010.

For the Ornstein–Uhlenbeck process of the Hicks-neutral productivity (or the managerial talents) of entrepreneurs, I set μ_z and σ_z such that the mean of the stationary distribution of $z_{i,t}$ is standardized to one, while the 75-to-25-percentile ratio equals 3.5, consistent with the TFPQ distribution of major industrial enterprises in 2010. Moreover, I set the mean-reverting rate of the process θ_z such that the evolution of the Hicks-neutral productivity is characterized by an autocorrelation of 0.995.

To bring the task-based technology to data, I assume the comparative productivity of capital services follows $\gamma(x) = x^A$. The economic interpretation is that, a 1% increase in task complexity (measured by index x) results in an A% reduction in the comparative productivity of industrial robots. Unlike Acemoglu and Restrepo (2018)'s specification, $\gamma(x) = exp(Ax)$, our formulation allows for variable elasticity of robot adoption relative to changes in robot prices. Acemoglu and Restrepo (2018)'s specification implicitly imposes a lower bound on elasticity that is too high compared to observed data.

I follow Humlum (2019) in adopting an elasticity of substitution across tasks, $\rho = 0.5$, indicating that different tasks are generally complementary. The productivity of the robotics industry in 2010, z^m_{2010}, is calibrated to match a robot-to-labour ratio of 0.003, corresponding to a density of around 30 industrial robots per 10,000 manufacturing workers in the automobile industry in China in 2010, as reported by the International Federation of Robotics. The comparative productivity parameter A is calibrated to match a 36% annual growth rate of industrial robot stock in China from 2010 to 2013, assuming an annual robot price reduction of around 8%.

For the estimation of financial frictions parameters, I follow the approach suggested

[12] see Atkeson and Kehoe (2007); Restuccia and Rogerson (2008)

by David and Venkateswaran (2019). More specifically, firms' maximization problem (8) implies:[13]

$$\frac{k_{i,t}}{l_{i,t}} = \frac{1-\alpha}{\alpha} \frac{[1+\Phi(a_{i,t})]r_t}{w_t}.$$

In practice, I estimate the structure of the borrowing cost term Φ with the following non-linear regression:

$$\log(\frac{k_i}{wl_i}) = \gamma + log(1+\beta a_i^{\omega}) + \mu_s + \epsilon_i. \tag{17}$$

Here, wl_i denotes the total payroll of firm i in 2010, and k_i and a_i denote the value of fixed assets and total assets respectively. I also include three-digit industry fixed effects μ_s to account for heterogeneous production technologies across different sub-industries. The estimation results indicate a significantly negative elasticity of $\omega = -0.7996$. It also indicates that manufacturing firms with an average level of total assets a_i in 2010 bore an additional cost of approximately 49.58% when utilizing capital. I calibrate the financial frictions scalar β to match the average scale of the capital usage restrictions.

7.3 Link to Empirical Findings

In order to study the impacts of the industrial robot subsidy implemented by the Chinese local governments, I feed exogenous changes in a uniform robot subsidy τ into the benchmark model and explore the consequences for aggregates and productivity. In the following section, I focus on the benchmark model with robotics industry productivity z^m equal to the 2017 level. Assuming an 8% annual growth in productivity, it yields $z^m_{2017} = 0.0172$.

Table 10 illustrates the percentage change for specific aggregates, relative to the benchmark scenario, given different magnitudes of robot subsidy. My analysis reveals that the robot subsidy significantly promotes industrial robot demand and positively impacts overall output. Specifically, Panel A of Table 10 shows that a robot subsidy of 20% results in

[13] Since there was a negligible number of industrial robots in 2010, I assume the fixed capital in 2010 is equivalent to traditional capital $k_{i,t}$ as in the model.

Table 9: Calibration Targets

Parameter	Value	Source/Targeted Moments
Preferences		
σ - EoS across varieties	7	Standard calibration
ϵ - Discount factor	3.00%	Capital to output ratio = 3
p - Dissipation rate	7.09%	Elasticity of capital supply $\approx$ 25
Technology		
α - Labour share in traditional technology	0.600	National Bureau of Statistics of China
δ - Depreciation	0.050	Standard calibration
ρ - EoS across tasks	0.500	Humlum (2021)
A - Comparative productivity of capital service	0.300	Annual growth rate of robot stock = 36%
z^m_{2010} - Robotics industry productivity in 2010	0.010	Robot density in 2010 = 0.003
μ_z - Mean of productivity process	-0.450	Mean of productivity standardized to one
σ_z - Diffusion of productivity process	0.095	Ratio of 75th to 25th percentile of productivity = 3.
θ_z - Mean-reverting rate of productivity process	0.005	Autocorrelation of productivity = 0.995
ν - Span of control	0.850	Standard calibration
c_f - Operating Cost	5.040	Average firm size in manufacturing = 58.15
Financial Frictions		
ω - Financial friction elasticity	-0.800	Estimation
β - Financial friction scalar	57.000	Firms with average total asset bear an extra cost of

a substantial 65.28% increase in industrial robot demand and an overall output growth of 1.23%. These results underscore the effectiveness of such subsidies in enhancing automation and boosting productivity across the manufacturing sector.

However, these benefits come at the expense of exacerbating the dispersion between small and large firms. First, the number of firms in the market decreases with the subsidy, showing a reduction of 1.27% under the 20% subsidy scenario. This indicates that a robot subsidy, while encouraging automation, also leads to small firms being edged out of the market. Second, Panels B and C of Table 10 show that the performance metrics for entrepreneurs exhibit a stark contrast: taking the 20% subsidy scenario as an example again, the top 10% of entrepreneurs experience significant improvements in turnover (5.34%), capital expenditure (22.67%) and profits (6.84%). In contrast, the bottom 50% of entrepreneurs suffer from shrinking market share and profits, with turnover and profits decreasing by 1.72% and 1.15%, respectively.[14]

[14] Top entrepreneurs are defined as those whose turnover falls within the top 10% of the overall turnover distribution, consistent with the definition of major industrial enterprises. Meanwhile bottom entrepreneurs are those whose turnover ranks in the bottom 50%.

Table 10: Changes of Numbers and Financial Performances of Firms in Robot Subsidy

Robot Subsidy τ	5%	10%	20%	30%
Panel A: Aggregates				
Industrial Robot Demand	13.12%	28.19%	65.28%	113.44%
Number of Firms	-0.02%	-0.07%	-1.27%	-2.56%
Output	0.32%	0.63%	1.23%	1.70%
Panel B: Top 10% Entrepreneur				
Turnover	1.20%	2.48%	5.34%	8.73%
Capital Expenditure	4.55%	9.76%	22.67%	40.03%
Employment	0.65%	1.34%	2.94%	4.96%
Profit	1.49%	3.11%	6.84%	11.43%
Average Asset Position	2.57%	5.31%	11.91%	21.72%
Panel C: Bottom 50% Entrepreneur				
Turnover	-0.58%	-1.29%	-1.72%	-3.43%
Capital Expenditure	-0.19%	-0.55%	-0.48%	-0.32%
Employment	-0.45%	-0.99%	-0.85%	-1.54%
Profit	-0.40%	-0.91%	-1.15%	-2.44%
Average Asset Position	1.37%	2.45%	5.74%	8.89%

Note: (1) Values represent percentage changes of outcomes relative to the benchmark model in response to 5%, 10%, 20% and 30% robot subsidy respectively; (2) Capital expenditure includes demand for traditional capital and industrial robots; (3) Panel B and C describe entrepreneurs with top 10% turnover and bottom 50% turnover respectively.

An important observation is that top firms significantly increase their labour demand following a subsidy, while bottom firms experience a reduction in employment. Under a 20% subsidy, employment in top firms rises by 2.94%, whereas bottom firms see a decrease of 0.85%. This suggests that the reduction in overall labour demand due to automation primarily occurs at the extensive margin, where large firms crowd out smaller ones. Consequently, while top firms expand and absorb more labour, smaller firms face increased competitive pressure, leading to shrinking labour demand.

Finally, the heterogeneous benefits received by entrepreneurs lead to increased dispersion in asset accumulation. Top entrepreneurs accumulate wealth much faster than their lower-tier counterparts. For instance, under a 20% subsidy, the average asset position of the top 10% of entrepreneurs increases by 11.91%, which is more than double the improvement in average asset position of the bottom 50% of entrepreneurs (5.74%). This growing disparity in asset accumulation underscores that the uneven impact of the subsidy is not merely static but is likely to be amplified through the dynamics of asset distribution. In summary, our model shows results that are consistent with the empirical findings.

7.4 Productivity Discussion

In this subsection, I discuss both the static and dynamic misallocation resulting from a uniform robot subsidy. More specifically, the dynamic misallocation accounts for the heterogeneous capital accumulation across entrepreneurs.[15] As described in Section 6, the effect of a subsidy can be decomposed into the mean automation efficiency effect and the automation dispersion effect. The mean of automation in Panel A of Table 11 measures the ratio of dispersion-purged automation to the socially optimal level in each scenario, which captures the mean automation efficiency effect. This metric demonstrates the effectiveness of a robot subsidy in correcting the inefficiently low industrial robot usage caused by financial frictions. For reference, the 0% subsidy benchmark scenario yields a mean automation level of around 35.76% of the optimal level. Column 6 of Table 11 shows that a 20% subsidy improves the mean automation of the economy by around 21.85 ppts, from the benchmark value to around 58% of the optimal level, which contributes to a rise in efficiency.

However, the use of a robot subsidy also exacerbates the dispersion of automation across firms. The STD of automation in Panel A of Table 11 measures the percentage change in the standard deviation of individual automation levels from the dispersion-purged level relative to the benchmark scenario. This metric captures the automation dispersion effect. It reveals that a 20% subsidy raises the dispersion by around 49%, indicating increased variability in how firms adopt automation when compared with the evenly distributed automation levels.

Overall, while a robot subsidy effectively boosts the economy's output, it is detrimental to TFP. A subsidy contributes to an increase in output of around 1.23% under the 20% scenario, but a decline in TFP of 2.40%. This decline in TFP highlights the productivity loss introduced by increased dispersion. I further measure the social welfare using a utilitarian approach with equal weights. My analysis shows that, on the basis of my current calibration of the existing financial frictions, a uniform robot subsidy can improve social welfare by around 0.23% when its magnitude is below or equal to 10%. However, if the subsidy goes

[15] See Hsieh and Klenow (2014); Bento and Restuccia (2017); Gopinath et al. (2017); Da-Rocha et al. (2023)

above 20%, its impact on welfare becomes negative. If the subsidy is as high as 30%, it significantly reduces welfare by around 3.22%, which illustrates that in such a scenario the efficiency loss due to automation dispersion balances out the gains from improving mean automation efficiency.

In this section with the full model, I differ from the analysis in Section 6, as I endogenize financial frictions by linking the idiosyncratic borrowing costs to the asset positions of heterogeneous entrepreneurs. This approach introduces an additional dynamic feedback mechanism of a robot subsidy through the dispersion of capital accumulation. As shown in Panel B of Table 11, the robot subsidy reduces wage while increasing interest rate and entrepreneurial profits. Since both young entrepreneurs and those experiencing low productivity shocks rely on reducing labour income to accumulate assets and overcome financial constraint, this shift results in a greater divergence in the speed of capital accumulation between poor and wealthier households, thereby exacerbating capital misallocation.

To quantify the dynamic misallocation resulting from a robot subsidy, I conduct a static counterfactual analysis for each subsidy scenario. In this exercise, I substitute the distribution of households $g(a, z)$ with the one from the benchmark framework, while keeping aggregate factor demands constant. I then compute the equilibrium aggregates and productivity measures. This method allows us to isolate the effect of the subsidy on aggregate factor usage, while removing the distributional impact on MPK wedges. The results of this practice are shown in the static columns in Table 11. By shutting down the dynamic mechanism, I effectively reduce the growth in capital returns and in entrepreneurial profits and the decline in wage rates, which narrows the income gap between wage earners and capital earners. That contributes to smaller automation dispersion and thus smaller TFP loss. My quantitative practice shows that, in the absence of distributional dynamics, the output gain from a robot subsidy increases from 1.23% to 1.60% in the 20% scenario. In general, the output gain can be 0.37% higher without the dynamic distortion.

Table 11: Changes of Automation and Productivity in Robot Subsidy

Robot Subsidy τ	5%	5% - Static	10%	10% - Static	20%	20% - Static	30%	30% - Static
Panel A: Measures of Efficiency								
Mean of Automation	39.51%	39.32%	44.17%	43.70%	57.61%	55.93%	79.70%	75.44%
STD of Automation	9.62%	9.52%	20.89%	20.64%	48.96%	48.35%	86.03%	84.32%
Output	0.32%	0.37%	0.63%	0.75%	1.23%	1.60%	1.70%	2.44%
TFP	-0.52%	-0.49%	-1.11%	-1.04%	-2.40%	-2.36%	-4.11%	-4.00%
Welfare (Utilitarian)	0.23%	-	0.23%	-	-0.58%	-	-3.22%	-
Welfare (Rawlsian)	-3.75%	-	-8.68%	-	-23.14%	-	-46.62%	-
Panel B: Factor Incomes								
Wage	-0.25%	-0.19%	-0.56%	-0.43%	-1.44%	-1.05%	-2.77%	-1.98%
Interest Rate	1.25%	1.12%	2.72%	2.43%	6.52%	5.81%	11.94%	10.61%
Average Profit	0.55%	0.64%	1.16%	1.35%	3.54%	3.00%	6.13%	4.93%

Note: (1) The 'Mean of Automation' row measures the deviation of dispersion-purged automation from the socially-optimal automation in different scenarios. For comparison, the value for the 0% subsidy benchmark case equals 35.76%, which indicates the mean automation level is around 64% below the efficient level; (2) The remaining rows measure percentage changes of outcomes relative to the benchmark model in different scenarios; (3) The 'TFP' row measures the gap between the actual output in the decentralized economy and the potential maximized output that could be produced with the same levels of aggregate inputs; (4) The 'Welfare (Utilitarian)' row is calculated with the Utilitarian approach, and the 'Welfare (Rawlsian)' row is calculated with the Rawlsian approach; (5) 'Static' columns are obtained by such static practice where I substitute the distribution of households $g(a, z)$ with that from the benchmark framework, while keeping aggregate factor demands constant.

8 Conclusions

This study assesses the impact of China's robot subsidy policies on the manufacturing sector. The study focuses on demand-side subsidies that incentivise firms to purchase robots. It uses a synthetic difference-in-difference approach applied to municipal-level data to identify the causal impact of the subsidies on robotics industry activities, and firm dynamics and financial performances of industrial enterprises.

The findings indicate that robot subsidy policies significantly boost robot innovation and expand the landscape of robotics firms. Specifically, they lead to a 13.6 percent increase in applications for robotics patents and a 29.5 percent increase in the number of robot production firms after the implementation of a robot subsidy policy. Despite being a uniform subsidy, it has markedly different effects on firms of different sizes and leads to a reduction in entry of new firms. Specifically, after the introduction of a robot subsidy policy, new firm entry decreased by approximately 14 percent. Concurrently, larger manufacturing firms saw notable increases in total assets (6.3 percent), turnover (7.8 percent) and employment (5.8 percent). This suggests that, while a subsidy facilitates access to robot technology, it tends to disproportionally benefit larger firms at the cost deteriorating firm dynamics. Consequently, such subsidies exacerbate existing inequalities, amplifying the advantages of larger firms.

I use a simple theoretical framework that incorporates borrowing costs into a task-based model to explain the empirical findings and elucidate the main efficiency trade-offs stemming from the introduction of a robot subsidy. My framework shows that financial constraints lead to suboptimal automation levels, particularly for firms with limited access to capital. Robot subsidies help to correct mean automation depression by increasing the average automation level of the economy from 40 percent to 58 percent of the socially optimal level, under a 20 percent subsidy scenario. However, subsidies also increase automation dispersion by around 48.96 percent, highlighting the trade-off between efficiency gains and increased dispersion.

To quantify the efficiency implications, I embed my static model into a dynamic heterogeneous agent framework. The calibration shows that a 20 percent subsidy leads to a 65 percent increase in industrial robot demand and a 1.23 percent increase in output. However, this comes at the cost of reducing total factor productivity (TFP) by 2.40 percent. In general, I find that a subsidy below or equal to 10 percent could contribute to a 0.23 percent increase in social welfare measured using a utilitarianism approach. Yet, if the subsidy goes above 20 percent, the automation dispersion dominates and the policy becomes detrimental to welfare.

In examining the dynamic misallocation implications, the study finds that robot subsidies exacerbate capital accumulation disparities. Wealthier entrepreneurs accumulate assets faster than their less affluent counterparts, leading to greater capital misallocation. This dynamic is reflected in the substantial increase in capital returns and entrepreneurial profits, accompanied by a decline in labour income. Shutting down this dynamic feedback channel can effectively reduce TFP losses and improve total output by another 0.37 percent under a 20 percent subsidy.

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