How Do Robot Subsidies Affect Aggregate Productivity And Firm Dispersion? Theory And Evidence From China

Yuxiao Hu Runhong Ma*

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Abstract

Despite the growing prevalence of industrial robots in manufacturing, few studies directly evaluate the aggregate and distributional effects of industrial policies that incentivize automation. This paper examines the impact of China's municipal-level robot subsidies, launched across cities amid an unprecedented wave of industrial robot adoption. We use a text recognition approach to compile a novel dataset of robot subsidy policies across municipalities. Employing a difference-in-differences design with synthetic matching weights, we find that robot subsidies significantly boost robot-related innovation and entrepreneurship but disproportionately benefit large manufacturing firms. Following the introduction of a subsidy, turnover among large enterprises increases by 7.8 percent, while new firm entry declines by 14.0 percent. These uneven effects are more pronounced in regions with severe financial frictions. To interpret these findings, we develop a stylized model in which endogenous automation interacts with financial frictions. The ability to endogenously adjust robot usage enables less financially constrained firms to exploit the uniform subsidy more effectively, which amplifies their productivity gains and expands their market share by crowding out more constrained firms. This mechanism generates an efficiency trade-off: while subsidies raise the average level of automation, they also widen dispersion across firms and exacerbate capital misallocation. Embedding this mechanism into a dynamic heterogeneous agent model calibrated to Chinese industrial data, we show that a 20 percent subsidy increases aggregate output by 1.2 percent but reduces total factor productivity by 2.4 percent. Overall, higher subsidy levels amplify misallocation and ultimately diminish aggregate efficiency.

Keywords: Industry Policy, Industrial Robot, Automation, Technology Adoption, Financial Frictions, Capital Misallocation, Heterogeneous Agent, Inequality.
JEL codes: E22, E23, O16, O25, O33

*Hu: Antai College of Economics and Management, Shanghai Jiao Tong University, Email: y.hu@sjtu.edu.cn; Ma: School of Finance, Renmin University of China, Email: r.ma@ruc.edu.cn. We are especially grateful to Silvana Tenreyro, Keyu Jin and Wouter Den Haan for their invaluable guidance and supervision throughout this project. We also thank Matthias Doepke, Jonathon Hazell, Dirk Krueger, Nan Li, Rachel Lukazs, Ben Moll, Rachel Ngai, Ricardo Reis, Zheng (Michael) Song, Dan Su, John Van Reneen, Yu Yi for helpful discussions, and numerous seminar and conference participants for their insightful comments and suggestions.

1 Introduction

Industrial policy has re-emerged as a central instrument of economic strategy. From the U.S. CHIPS Act to the European Green Deal, governments are increasingly intervening to support targeted industries (Barwick et al., 2025), stimulate innovation (Dechezleprêtre et al., 2023), and accelerate the energy transition (Banares-Sanchez et al., 2023). This revival reflects a recognition among governments that markets alone may not deliver the technological upgrading and productivity growth required in today's global economy. Understanding whether industrial policy works, how it operates, and what consequences it might induce has become an important question.

Among the wide array of industrial policies, we focus on robot subsidy policy in this paper. Industrial robots play a dual role in the modern economy and there is no clear consensus on whether they should be taxed or subsidized. On one hand, robots are seen as a potential threat to employment through labor displacement (Guerreiro et al., 2022; Beraja and Zorzi, 2025); on the other, they are regarded as a source of technological upgrading and productivity growth (Graetz and Michaels, 2018; Prettner and Strulik, 2020; Kapetaniou and Pissarides, 2025). This makes robot subsidies distinctive: unlike traditional industrial policies that target specific industries, robot subsidies intervene extensively in different departments of the manufacturing sector and, more importantly, directly in firms' technology adoption decisions. Hence, studying robot subsidies provides an opportunity to examine both the efficiency and distributional consequences of industrial policy in the context of technological change.

China provides an ideal setting to study the effects of robot subsidies. First, China has become the world's largest market for industrial robots, accounting for over 50% of global robot installations. This rapid growth has been driven by aggressive policy support, including national initiatives such as *Made in China 2025* and *the 14th Five-Year Plan for Robotics Industry Development*, along with hundreds of municipal-level subsidy programs. Second, previous studies show that

the industrial sector of China faces significant capital misallocation (Hsieh and Klenow, 2009; David and Venkateswaran, 2019), which allows us to explore how industrial policy interacts with existing distortions. Since the access to capital varies across firms, we are able to assess both the heterogeneous effects of robot subsidies at the firm level and their resulting aggregate consequences. Third, despite China's central role in the global robotics industry, research on the impact of its robot subsidy policy remains limited. To the best of our knowledge, this study is the first to investigate the impact of China's robot subsidy policy using both micro data and a general equilibrium model. These factors make China an ideal setting for evaluating both the distributional and aggregate impacts of robot subsidy policies.

This paper evaluates the effectiveness of robot subsidies in the context of financial frictions. Specifically, we focus on robot subsidies that provide financial support for the acquisition or rental of industrial robots. We follow three steps. First, we use a text-recognition approach to identify municipality-level robot subsidies and employ a difference-in-differences strategy to assess their effects on innovation and firm entry. We find that while the subsidies significantly boost robot-related innovation, the main beneficiaries are larger manufacturing firms, which see significant improvements in firm performance due to the subsidy. Second, we develop a simplified model that embeds the interaction between financial frictions and endogenous automation to account for these empirical patterns. We decompose the total welfare impacts of robot subsidies into two effects: (i) *Mean-Level Automation Gain* - the efficiency gains from higher aggregate robot adoption at the mean level in the economy; and (ii) *Automation Dispersion Loss* - the efficiency losses generated by firms adopting heterogeneous automation levels. Finally, we extend the model into a dynamic framework with heterogeneous households to quantify the efficiency trade-off. In counterfactual exercises, we evaluate the productivity and welfare effects of subsidies at different levels, attempt to decompose the static and dynamic misallocation induced by the subsidy, as well as embed the

model in a spatial setting to evaluate the spatial spillover of the subsidy.

In the first step of our analysis, we use a text-recognition approach (Juhász et al., 2022) to identify 244 municipal-level industrial robot subsidy policies from the Peking University (PKU) Law dataset. To be classified as a robot subsidy, a policy must include robot-related keywords, outline a comprehensive subsidy plan, and contain subsidy-specific terminology. These policies have three features: they are largely non-exclusive (over 85% impose no restrictions on firm size or qualifications), often incorporate local preferences (43.0% subsidize only the purchase or rental of robots produced by local firms), and are sizable, with an average subsidy rate of 17.5%.

Then, we empirically investigate the impact of robot subsidy policy. The main identification challenge is the potential endogeneity in the decision to launch the robot subsidy policy. For example, municipalities that introduced such subsidy might have different socio-economic characteristics, which also affect firm decision makings. To deal with the challenge, we employ both a traditional TWFE-DID specification and multiple alternative DID approaches (e.g., Arkhangelsky et al. 2021).

We present three empirical findings. First, the subsidy policy is effective in promoting robot-related activities. Following its introduction, applications for robotics patents have increased by 13.6 percent, and the number of robotics firms has increased by 29.5 percent. Dynamic event-study evidence further shows that these effects persist and intensify over time. Second, the subsidy disproportionately benefits major industrial enterprises[1]. After the policy, major industrial enterprises have experienced a 6.4 percent rise in total assets, a 7.8 percent increase in total revenue, and a 5.8 percent increase in employment. However, new firm entry has declined by about 14 percent after the policy. Third, we show that financial frictions amplify these heterogeneous effects. Using a municipality-level measure of financial frictions following David and Venkateswaran (2019), we find that asset accumulation among major industrial enterprises rises more in municipalities with higher

[1]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 (Annual Survey of Industrial Firms), these firms typically fall within the top 10 to 20 percent of the turnover distribution.

frictions (from 5.0 to 7.8 percent), while the decline in new firm entry is also more severe (from –9.4 to –14.0 percent). In other words, financial frictions magnify the distributional impacts of the policy: larger firms that benefit from economies of scale can further consolidate their advantage through easier access to robots, which crowds out potential new firm entries.

In the second step, motivated by the empirical findings, we develop a simplified framework that incorporates borrowing costs (Hsieh and Klenow, 2009) into a task-based model of endogenous automation (Acemoglu and Autor, 2012; Acemoglu and Restrepo, 2018). Introducing endogenous automation leads to heterogeneous effects of a uniform robot subsidy across firms: while all firms lower marginal costs through cheaper access to robots, less financially constrained firms achieve larger cost reductions because they are able to improve their robot adoption at greater scale and reallocate more tasks toward automation. This model explains our empirical findings that financially less constrained firms get more market share due to the uneven cost reduction. Based on this mechanism, we derive two implications of the robot subsidy policy. First, *Mean-Level Automation Gain*, which reflects efficiency gains from subsidies that raise the economy's mean level of automation toward the socially optimal benchmark absent financial frictions. Second, *Automation Dispersion Loss*, which refers to the efficiency losses that occur when a uniform subsidy induces uneven adoption across firms, which exacerbates the productivity loss from financial frictions.

In the third step, we extend the static model into a dynamic heterogeneous agent framework with endogenous occupational choice and capital accumulation. Building on the literature on dynamic misallocation (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Gopinath et al., 2017; Da-Rocha et al., 2023), we endogenize borrowing costs by linking them to entrepreneurs' heterogeneous asset positions (Moll, 2014; David and Venkateswaran, 2019). This extension reveals a dynamic mechanism whereby automation and robot subsidy exacerbate capital misallocation. We calibrate the benchmark model to match the productivity distribution, financial frictions, and robot

density and growth of robot stock from 2010 to 2013. Consistent with the empirical findings, larger firms increase turnover and employment by 5.34 and 2.94 percent, respectively, under a 20 percent subsidy. Our model also provides complementary quantification that is not attainable in the empirical analysis due to data limitations. Specifically, we find that a 20 percent subsidy raises robot demand by 65 percent and output by 1.23 percent, but reduces turnover and employment for smaller firms by 1.72 and 0.85 percent, respectively, leading to a 1.27 percent decline in the number of entrepreneurs. From an efficiency perspective, we are also able to quantify the *Mean-Level Automation Gain* and *Automation Dispersion Loss*. A 20 percent subsidy increases the mean automation level from 36 to 58 percent of the social optimum, but also raises the standard deviation of automation levels by 49 percent. As a result, automation dispersion losses outweigh the mean-level gains when the subsidy level exceeds a certain threshold. Overall, our model shows that a uniform robot subsidy can improve welfare (measured in a utilitarianism way) by around 0.23 percent when set at or below 10 percent, but begins to reduce welfare once its magnitude exceeds 20 percent.

We then conduct two extensions of the benchmark model. In the first extension, we decompose capital misallocation into static and dynamic parts. In line with Moll et al. (2022), a 20 percent subsidy raises the interest rate and entrepreneurial profits by 6.52 percent and 3.54 percent respectively, but reduces wages by 1.44 percent. The divergence of capital accumulation speed across entrepreneurs exacerbates capital misallocation in the long run, and hence induces TFP loss. If without the dynamic process, the output gain would increase by an extra 0.37 percent.

In the second extension, we embed the mechanisms into a spatial structure to examine regional spillovers of a local robot subsidy. We simulate two identical municipalities and apply a robot subsidy to one of them. The model reveals that, although the spillover city faces reduced robot investment due to rising national interest rates, it benefits from more even automation across firms

as well as falling local price levels. The practice implies a modest positive welfare spillover despite cross-region crowd-out effects.

Related Literature Our study contributes to three strands of literature. First, it adds to the empirical (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 (Aghion et al., 2015; Juhász et al., 2023), we assess the potential trade-offs of industrial policies. To our knowledge, this is the first study to analyze how China's large-scale robot subsidy policy increases the adoption of robotics technology yet exacerbates heterogeneity in adoption across firms.

Second, we contribute to the theoretical literature on endogenous automation adoption (Acemoglu and Autor, 2012; Acemoglu and Restrepo, 2018; Moll et al., 2022; Acemoglu, 2025) and policy interventions in automation. While many studies (Acemoglu et al., 2020; Beraja and Zorzi, 2025; Costinot and Werning, 2023) argue that robots should be taxed because adoption exacerbates inequality across agents (e.g., between capital owners and workers, or skilled and unskilled labor), a growing body of work emphasizes that restricting automation may hinder long-term growth and innovation (Prettner and Strulik, 2020; Gasteiger and Prettner, 2022; Guerreiro et al., 2022; Kapetaniou and Pissarides, 2025), and that well-designed subsidies can be welfare-improving (Caselli and Manning, 2019; Thuemmel, 2023). In contrast to this literature, which primarily focuses on inequality between individuals, our study examines inequality across firms. We show how robot subsidies generate uneven technology diffusion patterns between financially constrained and unconstrained firms (Berlingieri et al., 2025), and analyze the resulting implications for efficiency and productivity.

Third, our study contributes to the 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). We are among the first to examine how financial frictions shape endogenous automation decisions. From an efficiency perspective, we show that automation amplifies productivity losses arising from static capital misallocation, as highlighted in Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), and connects to 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). Our study also provides microfoundation for the strand of literature that attempt to quantify the role of factor share heterogeneity in misallocation (David and Venkateswaran, 2019; Asturias and Rossbach, 2023). Relatedly, Moll et al. (2022) demonstrates how automation magnifies wealth inequality through capital accumulation. Building on this insight, our study introduces a dynamic perspective to show how endogenous automation exacerbates dynamic capital misallocation.

The remainder of the paper is organized as follows. Section 2 provides an overview of China's robot subsidy policy. Section 3 presents facts on the effectiveness of subsidies in promoting robot-related activities and examines how manufacturing firms respond. Section 4 develops a simplified framework to analyze the mechanisms behind these patterns and the efficiency implications of a uniform robot subsidy. Section 5 embeds this framework into a dynamic model with heterogeneous entrepreneurs to quantify the effects on macroeconomic outcomes and efficiency. Section 6 concludes.

2 Research Background

According to the International Federation of Robotics, China's installation of new industrial robots has reached 290,300 units in 2022, which constitutes approximately 53% of the worldwide

installation of industrial robots for that year. At the same time, the total stock of robots in China has reached around 1.5 million units by 2022, which accounts for 38% of the global industrial robot stock. China has emerged as the world's leading user of industrial robots (Cheng et al. 2019) and a major contributor to their production.

The Chinese government's subsidy policies have played a pivotal role in driving the accelerated adoption of industrial robots in the country. Launched in 2015, the *Made in China 2025* initiative emphasizes the crucial role of industrial robots in China's industrial strategy. This ambitious policy sets an initial target of reaching 100 robots per 100,000 workers by 2020. Building on the *Made in China 2025* foundation, *the 14th Five-Year Plan for Robotics Industry Development* initiative, introduced in 2021, sets a more ambitious goal: to increase robot density to 500 units per 10,000 workers by 2025.

Demand-side robot subsidies serve as a key policy instrument. The subsidy policy encourages manufacturers to purchase or lease robots and offers subsidies that cover 5% to over 40% of the total cost or investment required. Typically, there are few stringent eligibility criteria, which renders the subsidies non-exclusive to a broad range of industrial enterprises. In Section 3.1, we further explain how we identify robot subsidy policy and introduce some key statistics about the policy.

While *the Made in China 2025* initiative and *the 14th Five-Year Plan* initiative outline the national strategy, the actual implementation of robot subsidy policies largely falls under the jurisdiction of local governments, as noted by Bai et al. (2020). According to Figure A2, the number of municipalities adopting demand-side robot subsidies has significantly increased. In 2014, only two municipalities have implemented such subsidies, but by 2023, this number had grown to 93, approximately 32% of all municipalities in China.

Figure 1 illustrates the geographic distribution of robot subsidy implementation and the number of robotics patent applications across China from 2010 to 2018. Municipalities with red borders

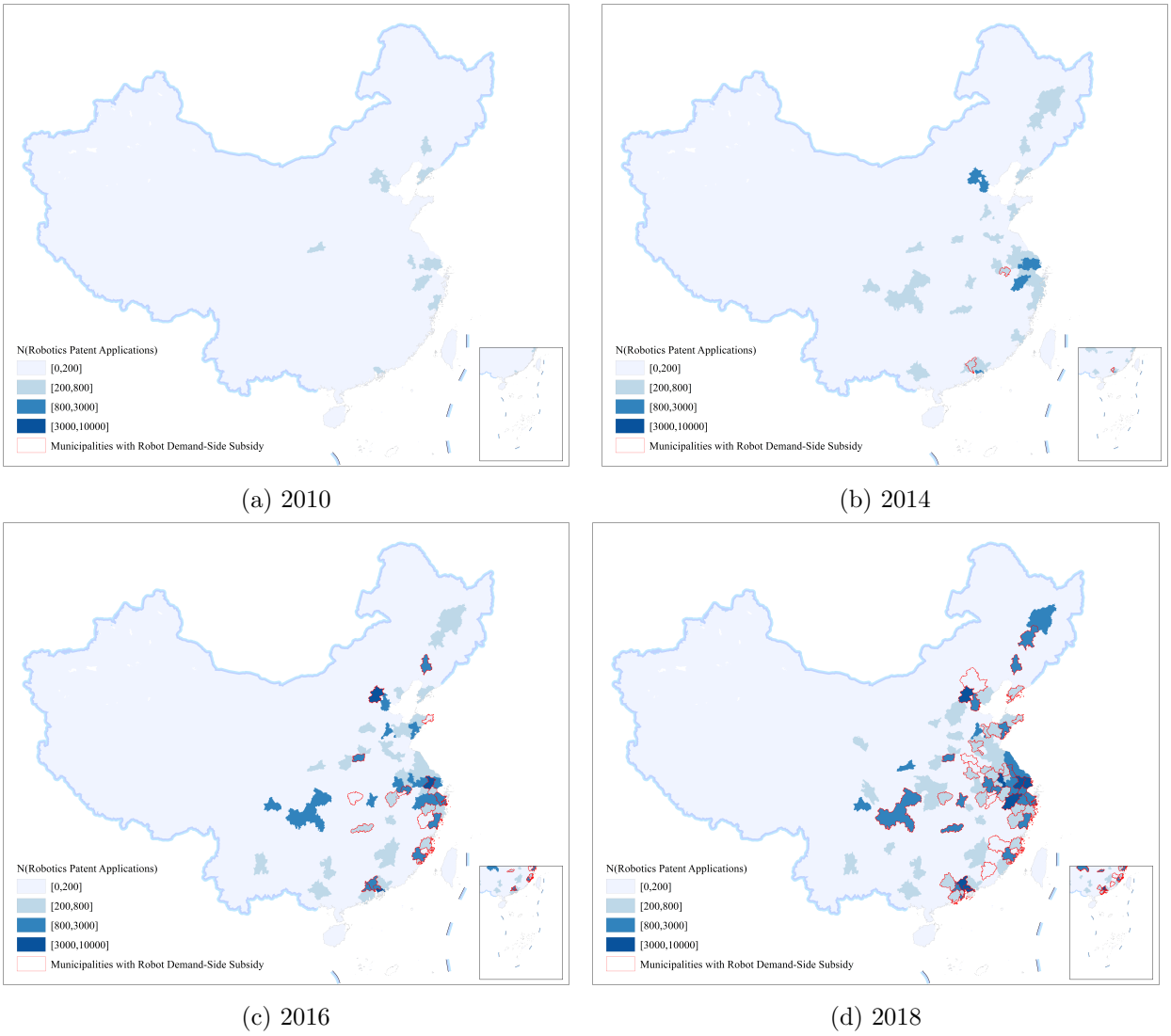
indicate those that have implemented robot subsidies, while darker shaded regions represent municipalities with a higher number of robotics patent applications. Panel (a) shows that in 2010, the concentration of patent applications was relatively low, and the action of subsidizing the usage of industrial robot has yet begun. In 2014, as seen in panel (b), there is a modest increase in the number of municipalities with robot subsidies and a corresponding rise in patent applications in these regions. This trend becomes more evident in panel (c) for 2016, where the introduction of subsidies seems to coincide with increased local innovation, as reflected by the denser patent applications in municipalities with subsidies. By 2018, as shown in panel (d), both the geographic spread of robot subsidies and the number of patent applications have expanded significantly. Municipalities with robot subsidies, marked by the red borders, consistently exhibit higher levels of innovation. These descriptive results suggest that the introduction of robot subsidies may be linked to an increase in local robot-related patenting activity. In Section 3, we present empirical evidence to further support the claim that the robot subsidy policy has contributed to a rise in robot-related innovation activities.

3 Empirical Investigation

3.1 Identifying Robot Subsidies using Text-Recognition Approach

To assess the impact of increased robot usage on the manufacturing sector, we focus on robot subsidy policies that incentivize manufacturers to acquire or lease industrial robots. We identify relevant policies using the PKULaw dataset, which compiles laws and administrative documents issued by Chinese local and central governments since 1949. By applying a text-recognition algorithm to extract municipal-level policies, we locate robot subsidies that offer direct financial subsidies for robot acquisition or rental.

Specifically, a policy is classified as a robot subsidy policy if it meets three criteria across three



(a) 2010 (b) 2014

(c) 2016 (d) 2018

Figure 1: Geographic Distribution of Robot Subsidies and Robotics Patent Applications in China Time Period: 2010-2018

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.

consecutive paragraphs in the contents: (i) it includes keywords related to robotics, automation, or smart technology; (ii) it specifies the amount of financial assistance per unit; and (iii) it explicitly refers to the assistance as a subsidy. See Online Appendix B.1.1 for more details.

Using this approach, we identify 244 municipal-level robot subsidy policies issued between 2014

and 2023. These policies exhibit three key features. First, they are largely non-exclusive: over 86.9% impose no restrictions on firm size or qualifications. Second, they show strong local preferences: 43.0% subsidizes the purchase or rental of robots produced by local firms. Third, the subsidies are sizable, with the average subsidy rate reaching 17.5%. Given an average unit price of $40,000 for industrial robots, this translates to an average subsidy of approximately $8,000 per unit. See Online Appendix B.1.2 for more details.

3.2 Empirical Strategy

We first employ a traditional two-way fixed effects (TWFE) approach to estimate the impact of the municipality-level subsidy policy. The treatment is defined as a municipality starting to implement the robot subsidy policy. Accordingly, a municipality is considered treated from the year it has started to implement the policy. We first use the standard Two-Way-Fixed-Effects (TWFE) approach to investigate the impact of the robot subsidy policy. The regression specification takes the form of:

$$Y_{it} = \alpha + \beta \times RobotSubsidy_{it} + \gamma_i + \lambda_t + \epsilon_{ikt},$$

where Y_{it} measures the outcome of interest in municipality i, and year t, the treatment variable $RobotSubsidy_{it}$ is a dummy variable that equals one for municipality i that has implemented the robot demand-side subsidy policy before year t, and 0 otherwise. The coefficient β measures the impact of the subsidy on municipality-level outcomes. We include municipality fixed effects γ_i and year fixed effects in all regressions, and cluster standard errors at the county level.

To test whether those municipalities with robot subsides and our control municipalities have similar trend prior to the implementation of the subsidies, we estimate event studies of the form:

$$Y_{it} = \alpha + \sum_{\tau=-5, \tau\neq-1}^{5} \beta_\tau \times 1[t = \tau + T_{ik}^{Subsidy}] + \gamma_i + \lambda_t + \epsilon_{it}.$$

In this specification, $T_{ik}^{Subsidy}$ denotes the calendar year when municipality i implemented robot demand-side subsidy for the first time. β_τ represents differences in the outcome variables between the municipalities that have implemented the robot subsidy and control municipalities in each year.

A major potential concern arises in the standard TWFE approach. The adoption of robot subsidy policy may not be random, which could bias our estimates. Table B3 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 labor market conditions. Our analysis highlights the role of fiscal capacity, educational resources, the ex-ante industrial structure 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 wherewithal and the readiness of local industries to integrate robotics into their operations. This aligns with the observation in Figure 1 that wealthier provinces in southeast China are often at the forefront of the implementation of demand-side robot subsidies. To address this concern, we use the DID estimator with matching weights (Arkhangelsky et al., 2021), which combines attractive features of traditional difference-in-differences (DID) with the method of synthetic controls (SC) (Abadie et al., 2010). As in the SC approach, this approach balances treated and control units on pre-treatment outcomes and limits researcher discretion in estimating pre-trends (e.g., the choice of covariates, time periods, or deliberate choice of control units). This approach mitigates possible concerns noted by Roth et al. (2023) and generally outperforms standard DID in avoiding spurious significance (Arkhangelsky et al., 2021). We also implement alternative difference-in-differences estimators proposed by de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021). Our results remain robust across specifications.

3.3 Three Facts

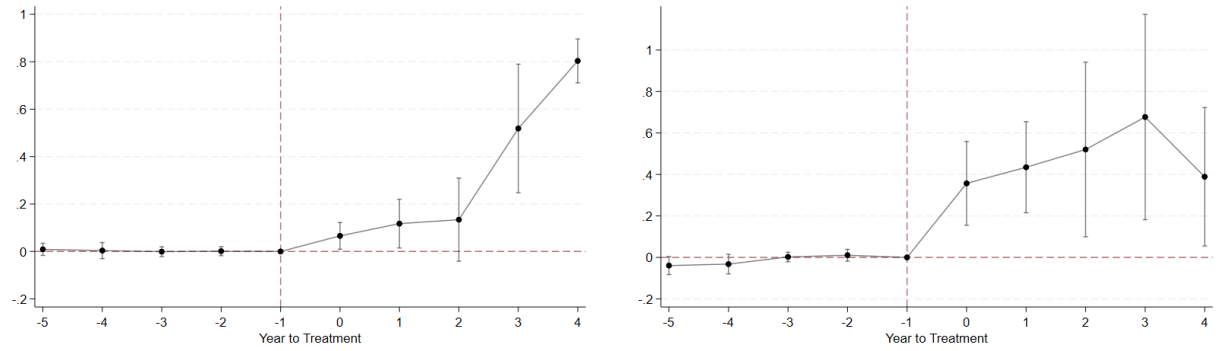
3.3.1 Fact I. Robot Subsidy Causes Increases in Robot-Related Activities

We begin our empirical analysis by evaluating whether the robot subsidy policy is effective in promoting robot-related activities, including robot-related innovation and entrepreneurship.

Data. We collect patent application data from the China National Intellectual Property Administration for the period 2010–2018. Using a text-recognition approach, we identify robotics patents based on two criteria: (i) the presence of keywords related to industrial robots (e.g., "robot," "robot arms"); or (ii) terms associated with robot modules (e.g., "servomotor," "reducer"). On average, municipalities with robot subsidies record 280 robotics patent applications per year, compared to 29 in those without. See Online Appendix B.1.3 for more details.

We also obtain business registration data from the National Enterprise Credit Information Publicity System (NECIPS) for the same period. Robotics firms are identified as manufacturing businesses with "industrial robot" in their stated business scope. We specifically focus on firms in machinery, electronics, and information technology sectors due to their relevance to robotics. On average, municipalities with subsidies record 26 new robotics firm entries per year, compared to 3 in those without.

Results. Panel A of Figure 2 shows that, prior to the introduction of the subsidy, there was no significant difference in robotics patent activity between subsidized and unsubsidized municipalities. After the subsidy was implemented, subsidized municipalities experienced a sustained and significant increase in robotics innovation, compared to non-subsidized municipalities. Consistently, Columns (1) - (3) in Panel A of Table 1 report that the policy has increased total robotics patent applications by 13.6%, with larger effects for patents related to robot units (18.7%) than those related to robot modules (13.3%). Similarly, Panel B of Figure 2 indicates that the robot subsidy policy has a persistent and significant impact on the number of new robotics firms. Cor-



(a) Number of Robotics Patents (b) Number of Robotics Firm Establishment

Figure 2: Dynamic Impacts of Robot Subsidy on Robot-Related Activities

Note: (1) The figure depicts the event study coefficients from DID approach as described in Section 3.2; (2) 'Robotics Patents' refer to all patent applications related to industrial robots and robot-related modules; (3) 'Robotics Firm Establishment' refers to the number of newly-established machinery-manufacturing enterprises that produce industrial robots as their major businesses; (3) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (4) Treatment is the implementation of a municipality-level robot subsidy policy; (5) All regressions include municipality and year fixed effects; (6) Standard errors are clustered at the municipality level; (7) 95% confidence intervals are plotted around point estimates.

respondingly, Column (1) in Panel B of Table 1 shows that the robot subsidy policy leads to a 29.5% increase in robotics firm entry in subsidized municipalities. We further examine robotics firms in three sectors-machinery, electronics, and electric equipment-given their close connection to robotics production and integration (IFR, 2023). According to columns (2) - (4) in Panel B or Table 1, sector-specific effects show increases of 43.2% in machinery, 26.4% in electronics, and 35.6% in electric equipment following the introduction of the subsidy.

Robustness Checks. While the Synthetic DiD (SDID) approach of Arkhangelsky et al. (2021) serves as the main identification strategy, we also report estimates in Figures B5 and B6 using three alternatives: traditional TWFE, the heterogeneous treatment effects model by De Chaisemartin and d'Haultfoeuille (2020), and the multiple-period DiD method by Callaway and Sant'Anna (2021). Online Appendix B.2 presents the results. All methods yield post-treatment effects consistent with those shown in Figure 2, supporting the robustness of the main results.

Table 1: Impact of the Municipality-Level Robot Subsidy on Robot-Related Activities

Variables (in IHS)	Robotics Patents	Robotics Patents by Type:		All Patents
		Robot Units	Robot Modules	
	(1)	(2)	(3)	(4)
Panel A. Robotics Patents				
Robot Subsidy	0.136**	0.187***	0.133**	0.030
	(0.062)	(0.068)	(0.069)	(0.049)
Observations	2,538	2,538	2,538	2,538
Variables (in IHS)	Robotics Firms	Robotics Firms by Industry:		
		Machinery	Electronic	Electric
	(1)	(2)	(3)	(4)
Panel B. Robotics Firm Entry				
Robot Subsidy	0.295***	0.432***	0.264***	0.356***
	(0.091)	(0.108)	(0.096)	(0.092)
Observations	2,538	2,538	2,538	2,538
For All Panels:				
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y

Note: (1) We use the difference-in-differences estimation (see Section 3.2 for detailed discussion); (2) Treatment is the implementation of a municipality-level robot subsidy policy; (3) 'Robot Units' refers to patents of robot whole unit 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); (4) 'All Patents' refer to the patent application of all categories, including but not limited to robotics patents; (5) 'Robotics Firms' refers to all robotics firms in the manufacturing sector, 'Machinery', 'Electronic' and 'Electric' categories cover robotics firms classified into corresponding sub-industries; (6) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (7) Standard errors are clustered at the municipal level; (8) *, **, and *** respectively indicates 10%, 5%, and 1% significance level.

3.3.2 Fact II. Robot Subsidy Disproportionately Benefits Larger Firms

The previous section demonstrated that robot subsidies effectively promote robot-related activities. This section explores their broader impact on manufacturing firms. We find suggestive evidence that the policy shifts gains from the extensive to the intensive margin by discouraging new firm entry while disproportionately benefiting larger firms.

Data. We use firm-level data from the Annual Survey of Industrial Enterprises (ASIE), which includes all state-owned industrial enterprises and private firms with annual sales above 20 million

RMB (approximately 3.3 million USD). The dataset provides detailed information on inputs, outputs, sales, taxes, and profits, which allows us to assess the impact of robot subsidies on firm-level outcomes.

Results. Panel A of Figure 3 shows the DiD coefficients when the outcome variable is the number of newly established manufacturing firms. We find that firm entry declines following the introduction of the robot subsidy, with the downward trend persisting over time. Column (1) of Panel A in Table 2 estimates a 14% reduction in new firm entry in municipalities that adopted the policy. These results remain robust across different industries, and exacerbate when zooming into industries of higher automation exposure, including machinery, automobile, and electronic production (IFR, 2023).

In contrast, Panels B - D of Figure 3 reveal positive effects for major industrial enterprises with annual turnover exceeding three million USD. These firms experience significant increases in turnover, total assets, and employment. Column (1) of Panel B in Table 2 shows no significant change in the number of major firms. The results suggest that the policy operates through the intensive rather than extensive margin. Specifically, the policy leads to a 6.4% increase in total assets, a 7.8% increase in turnover, and a 5.8% increase in employment among major industrial enterprises.

Robustness Checks. We also report our robustness-check estimates in Figures B7 - B10 using three alternatives: traditional TWFE, the heterogeneous treatment effects model by De Chaisemartin and d'Haultfoeuille (2020), and the multiple-period DiD method by Callaway and Sant'Anna (2021). Online Appendix B.2 presents the results. All methods yield post-treatment effects consistent with those shown in Figure 3.

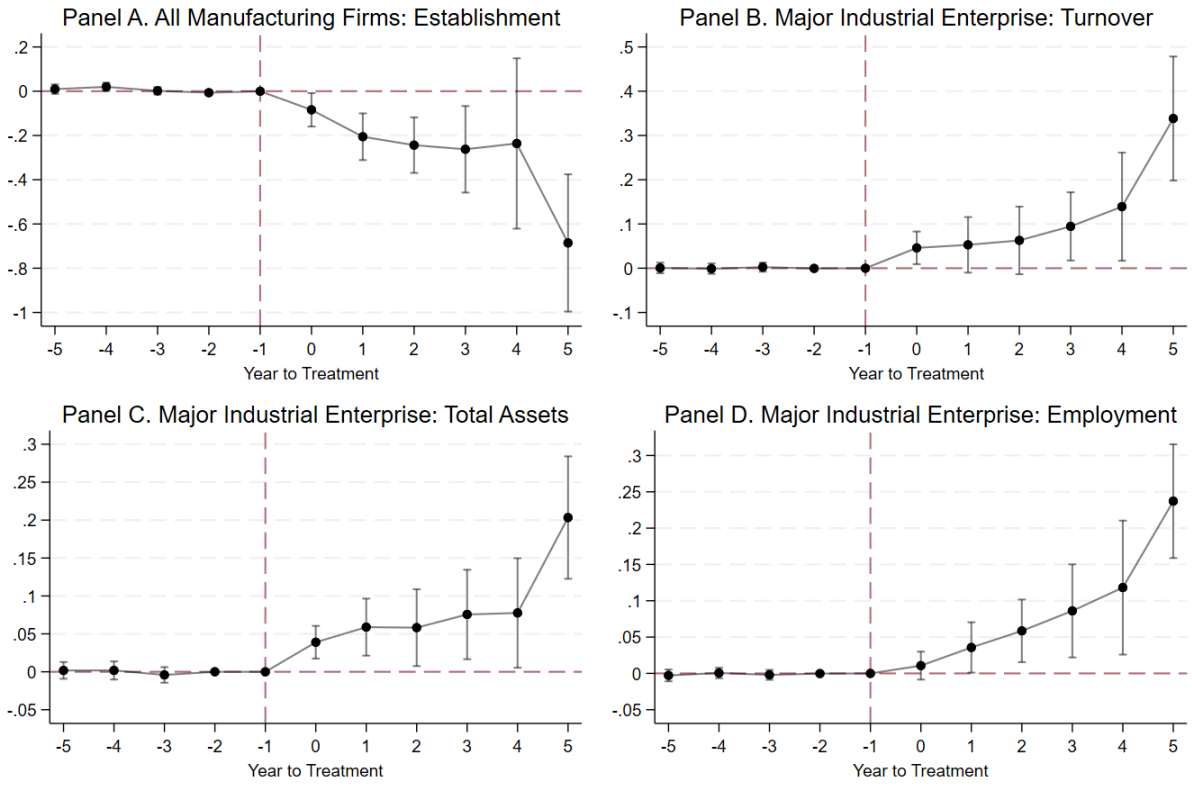


Figure 3: Dynamic Impacts of Robot Subsidy on Performance of Industrial Enterprises

Note: (1) The figure depicts the event study coefficients from DID approach as described in Section 3.2; (2) 'All Manufacturing Firm: Establishment' refers to the total number of newly-established manufacturing enterprises; (3) Major industrial enterprises refer to firms with annual sales exceeding 20 million RMB (approximately 3.3 million USD); (4)'Major Industrial Enterprise: Turnover' refers to the annual turnover of major industrial enterprises in a municipality; (5) 'Major Industrial Enterprise: Total Assets' refers to the total assets of major industrial enterprises in a municipality; (5) 'Major Industrial Enterprise: Employment' refers to the number of employees of major industrial enterprises in a municipality; (6) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (7) Treatment is the implementation of a municipality-level robot subsidy policy; (8) All regressions include municipality and year fixed effects; (9) Standard errors are clustered at the municipality level; (10) 95% confidence intervals are plotted around point estimates.

3.3.3 Fact III. Financial Frictions and the Distributional Impact of Robot Subsidy

In this section, we empirically examine how financial frictions contribute to the uneven distribution of benefits across firms. The existing literature identifies firm-specific distortions like financial frictions as a dominant constraint in China's industrial sector (David and Venkateswaran, 2019). To investigate this mechanism, we first construct a municipality-level measure of financial frictions for the year 2013, one year before the introduction of China's first robot subsidy in 2014. We then

Table 2: Impact of Municipality-Level Robot Subsidy on Industrial Enterprises

Variables (in IHS)		by Type:		
	Total	Machinery	Automobile	Electronic
	(1)	(2)	(3)	(4)
Panel A. Manufacturing Firm Entry				
Robot Subsidy	−0.140**	−0.190***	−0.283***	−0.367***
	(0.058)	(0.070)	(0.092)	(0.088)
Observations	2,538	2,538	2,538	2,538
Variables (in IHS)	Count	Total Asset	Turnover	Employment
	(1)	(2)	(3)	(4)
Panel B. Performance of Major Industrial Enterprise				
Robot Subsidy	0.015	0.064***	0.078**	0.058**
	(0.025)	(0.016)	(0.036)	(0.025)
Observations	2,538	2,538	2,538	2,538
For All Panels:				
Fixed Effects				
Year	Y	Y	Y	Y
Municipality	Y	Y	Y	Y

Note: (1) We use the difference-in-differences estimation (see Section 3.2 for detailed discussion); (2) Treatment is the implementation of a municipality-level robot subsidy policy; (3) 'Total' refers to all firms in the manufacturing sector, 'Machinery', 'Automobile', 'Electronic' and 'Electric' categories cover firms classified into corresponding sub-industries; (4) '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; (5) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (6) Standard errors are clustered at the municipal level; (7) *, **, and *** respectively indicates 10%, 5%, and 1% significance level.

compare the extent of disproportionate benefits from the subsidy between municipalities with the higher and lower levels of financial frictions.

Measuring Financial Frictions at the Municipal Level. We measure the magnitude of financial frictions at the municipal level using the following profit-maximization setup:

$$\max_{\{k_i,l_i\}} \; z_i k_i^{\alpha_s} l_i^{1-\alpha_s} - \tau_{i,c} r_c k_i - w_c l_i$$

The above optimization problem describes an industrial firm i that maximizes its profit subject

to sector-specific factor shares α_s and local factor prices r_c and w_c. The first-order condition implies:

$$ARPK_i = \frac{\tau_{i,c} r_c}{\alpha_s},$$

where $ARPK_i$ represents the average revenue product of capital for firm i. $\tau_{i,c}$ captures the idiosyncratic financial frictions faced by firm i in municipality c. We assume that these financial frictions vary with the firm's asset position a_i according to a municipal-specific elasticity β_c:

$$\tau_{i,c} = \omega a_i^{\beta_c}$$

Therefore, β_c serves as a measure of financial frictions at the municipal level. Intuitively, the presence of financial frictions results in a negative β_c, indicating that firms with larger asset positions face lower costs in utilizing capital. Moreover, a more negative β_c suggests greater dispersion in firms' capital access costs, implying more severe financial frictions in municipality c. We estimate β_c using the following econometric model:

$$arpk_i = \gamma + \beta_c \log(a_i) + \mu_s + \mu_c + \epsilon_i, \tag{1}$$

where $arpk_i = \log(\frac{P_i Y_i}{k_i})$, with $P_i Y_i$ denoting firm i's annual revenue, and k_i and a_i representing its fixed and total assets, respectively. We include the three-digit industry fixed effect μ_s and municipality fixed effect μ_c. The estimation relies on the 2013 Major Industrial Enterprise Database.

The estimated values of β_c for 286 municipalities are all negative and statistically significant. The 5th and 95th percentiles of β_c are -0.686 and -0.275, respectively, indicating substantial variation in financial frictions across municipalities. The average β_c is -0.469, implying that a 1% increase in total assets reduces the MPK wedge by 0.47 percentage points, highlighting the role of financial frictions in constraining capital use in the context of China's industrial sector.

How Financial Frictions Explain Disproportionate Benefits of Robot Subsidy. Next, we zoom into the treated municipalities. Among the 63 municipalities that introduced the robot subsidy, the average β_c is -0.430, with the 5th and 95th percentiles at -0.574 and -0.297, respectively. This pattern suggests that municipalities with lower ex-ante financial frictions were more likely to adopt the subsidy. We then classify the treated municipalities into two groups: those with stronger financial frictions (bottom 50% of β_c) and those with weaker financial frictions (top 50% of β_c).

Table 3 summarizes the estimated effects of the robot subsidy on manufacturing firm entry and the total assets of major industrial enterprises. Panel A shows that in municipalities with more severe financial frictions, the decline in manufacturing firm entry due to the subsidy is larger, increasing from -9.4% to -18.0% compared to municipalities with weaker financial frictions. Panel B reveals a similar pattern for total asset accumulation among larger firms, where the subsidy's impact is stronger in municipalities with more severe financial frictions, rising from 5.0% to 7.8%.

4 A Simplified Model Exploring Distributional Impacts of Uniform Robot Subsidy

Before delving into the full model, we will first describe a simplified environment that incorporates exogenously-given borrowing costs in the form of MPK wedges (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. We will then discuss the impact of a uniform robot subsidy on automation dispersion and how the interplay affects overall productivity through static misallocation (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Our simplified model abstracts from specific microfoundation of the borrowing costs in pursuit of mathematical tractability. In the full model, we will introduce heterogeneous entrepreneurs with endogenous the borrowing costs to account for the

Table 3: Impacts of Subsidy Policy on Municipalities with Different Levels of Financial Frictions

Variables (in IHS)		by Levels of Financial Frictions:	
	All	*Strong*	*Weak*
	(1)	(2)	(3)
Panel A. Manufacturing Firm Entry			
Robot Subsidy	−0.140**	−0.180***	−0.094
	(0.058)	(0.086)	(0.086)
Variables (in IHS)		by Levels of Financial Frictions:	
	All	*Strong*	*Weak*
	(1)	(2)	(3)
Panel B: Total Asset of Major Industrial Enterprises			
Robot Subsidy	0.064***	0.078***	0.050*
	(0.016)	(0.021)	(0.023)
For All Panels:			
Fixed Effects			
Year	Y	Y	Y
Municipality	Y	Y	Y

Note: (1) We use the difference-in-differences estimation (see Section 3.2 for detailed discussion); (2) Treatment is the implementation of a municipality-level robot subsidy policy; (3) We explain how we measure financial friction in Section 3.3.3, 'Strong Financial Frictions' column includes municipalities with bottom 50% β_c, 'Weak Financial Frictions' column includes municipalities with top 50% β_c; (4) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (5) Standard errors are clustered at the municipal level; (6) *, **, and *** respectively indicates 10%, 5%, and 1% significance level.

quantitative implications of dynamic misallocation (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Gopinath et al., 2017; Da-Rocha et al., 2023) through endogenous capital accumulation.

4.1 Environment

Households

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

$$V(a_0) = \max_{\{c_t, a_{t+1}\}} \sum_{t=0}^{\infty} \beta^t u(c_t), \qquad (2)$$
$$\text{s.t.} \quad c_t + a_{t+1} = (1 + r_t)a_t + w_t + \pi_t - T_t,$$

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 a lump-sum tax which will be introduced later.

Final Good

There is a unit mass firms $i \in [0, 1]$ operating in the economy. The final good and the numeraire is produced by aggregating varieties supplied by firms using a CES technology:

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

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

Production Sector

Task-Based Framework To endogenize the adoption of industrial robots, we 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 $j \in [0, 1]$. Capital and labor are considered perfect substitutes across tasks:[2]

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

Here, $\gamma(j)$ represents the relative productivity of labor in performing task j, which is assumed to be strictly increasing in j to capture increasing comparative advantage of labor in performing more complex tasks. Firms produce varieties using a CES production technology with elasticity $\rho \in (0, 1)$:

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

[2]For simplicity, we assume the absence of technological constraints, implying that all tasks are fully automatable.

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 labor. 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 We assume the firms face financial frictions in the form of idiosyncratic borrowing costs Φ_i (Hsieh and Klenow, 2009; Moll et al., 2017; David and Venkateswaran, 2019).[3] We further posit that $\{\Phi_i\}_{i\in[0,1]}$ follows an exogenously-given distribution such 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. We will endogenize the borrowing costs in the full model.

Uniform Robot Subsidy As per the industrial robot subsidy policies enacted by Chinese municipalities, we 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:

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

[3] While industrial enterprises in China face significant capital misallocation arising from multiple sources, we 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).

Government Budget Constraint

The robot subsidy is financed by a lump-sum tax collected from the firms. Hence, the government budget balance is given by equalizing the lump-sum tax T_t with the robot subsidy expenditure:

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

Market Clearing Conditions

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

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

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

Firms' prices $p_{i,t}$ aggregate to the final good price, which equals one as the numeraire:

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

Equilibrium

The competitive equilibrium of the economy consists of household's consumption c_t and lump-sum tax T_t, firms' automation levels $J_{i,t}$, outputs and factor demands $y_{i,t}$, $k_{i,t}$ and $l_{i,t}$, and prices w_t, r_t and $p_{i,t}$ 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 2;

2. $J_{i,t}$, $y_{i,t}$, $k_{i,t}$ and $l_{i,t}$ satisfy firms' profit maximization problem 3;

3. w_t and r_t satisfy factor market clearing conditions 5 and 6, and $p_{i,t}$ satisfy the one-price principle 7;

4. T_t satisfies the government budget balance condition 4.

4.2 Link to Empirical Findings

In this section, we explore the interaction between idiosyncratic borrowing costs and firms' decisions to automate and explain how this interplay helps to explain our empirical observations.

Lemma 1 *The optimal automation level of firm i is given by $\gamma(J_i) = \frac{w}{(1-\tau)(1+\Phi_i)r}$. Then, in response to a rise of the uniform automation subsidy $d\tau$, the change of marginal cost, mc_i, can be described by:*

$$\frac{\partial \log mc_i}{\partial \tau} = -\frac{J_i}{J_i + \gamma(J_i)^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}\frac{1}{1-\tau},$$

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

Proof. See Online Appendix C.

Lemma 1 establishes that a uniform subsidy τ consistently lowers firms' marginal costs, though the magnitude of this effect varies across firms. In particular, firms facing weaker borrowing constraints benefit more from the subsidy. This heterogeneity arises because firms optimally choose their ex-ante automation levels J_i based on the idiosyncratic financial constraint they are faced with, resulting in dispersion in automation and thus in productivity gains. The following proposition characterizes the equilibrium effects of this uniform automation subsidy.

Proposition 1 *Assume the wealth effect is sufficiently small such that $\frac{\partial Y}{\partial \tau} \approx 0$, then there always exists a cutoff value for the borrowing costs, $\bar{\Phi}$, such that*

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

where $share_i$ denotes the market share of firm i. Then $\frac{\partial p_i y_i}{\partial \tau} > 0$ and $\frac{\partial \pi_i}{\partial \tau} > 0$ if and only if $\Phi_i < \bar{\Phi}$.

Proof. See Online Appendix C.

Proposition 1 demonstrates how the benchmark framework helps reconcile the empirical patterns observed in the data.[4] Firms with better access to capital ($\Phi_i < \bar{\Phi}$) benefit disproportionately from

[4]We abstract from wealth effects to simplify the analysis. As the full model will later show, the qualitative implications remain valid even when these effects are incorporated in the context of China.

an increase in the uniform subsidy τ, which enables them to improve their turnover and market share at the expense of financially constrained competitors. In contrast, firms facing tighter financial conditions ($\Phi_i > \bar{\Phi}$) tend to experience profit declines following the subsidy. 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.

What we would like to highlight is that, endogenous automation is one essential elements that contributes to the unequal gains described in Proposition 1. Lemma 1 shows that, if all firms adopted identical automation levels J_i, as in standard CES production technology, the marginal cost reduction would also be uniform across firms. In that case, there would be no reallocation of market share or differential changes in turnover and profits in response to a uniform robot subsidy across firms. Hence, it is precisely the heterogeneity in automation, arising endogenously from idiosyncratic financial costs, that drives the uneven impacts of the subsidy.

4.3 Productivity and Efficiency Discussion

In this section, we explore the productivity and efficiency implications of a uniform robot subsidy in the presence of financial frictions and endogenous automation adoption. Our analysis reveals that idiosyncratic financial costs 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, We 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, we assume the elasticity of substitution between tasks $\rho = 1$, which reduces the production function to a Cobb-Douglas form:

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

Three Important Automation Measures

Before discussing the efficiency and productivity implications, we 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 the last section. The socially-optimal automation level J_t^* is obtained from the following equation, where we assume there is no distortive MPK wedges or robot subsidy:

$$\gamma(J_t^*) = \frac{w_t}{r_t}$$

The socially-optimal automation level J_t^* is identical for all firms. That is because the optimal level of automation depends solely on the factor prices, which are identical across firms in the absence of idiosyncratic financial costs. We refer to this uniform automation level 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, we need to derive a *dispersion-purged automation level*, $\bar{J}_t$, which is another 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, we 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, we

evaluate the efficiency loss due to automation dispersion across firms.

This hypothetical automation level, the dispersion-purged automation level $\bar{J}_t$, is derived from the dispersion-purged problem defined as follows:

Optimization 2 *(Dispersion-Purged Problem)*

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

Here, K_t^{DE} and L_t^{DE} denote capital and labor demands in the decentralized economy. By solving Optimization 2 we obtain an equation that determines dispersion-purged automation level $\bar{J}_t$:

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

The dispersion-purged problem aims to maximize the total 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^{DE} and L_t^{DE}, we 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, we now consider how a marginal increase in a uniform robot subsidy τ affects the value function of the representative household $V(a_t; \{\Phi_i\}_{i\in[0,1]}, \tau)$ given existing financial costs $\{\Phi_i\}_{i\in[0,1]}$:

Proposition 2 *The marginal change of the representative household's value function resulting from a marginal rise of the uniform robot subsidy τ at time t can be described by:*

$$\frac{\partial V(a_0, \{\Phi_i\}_{i\in[0,1]}, \tau)}{\partial \tau} = \sum_{s=0}^{\infty} \beta^s \lambda_{t+s} I_{t+s}.$$

Here, λ_{t+s} denotes the stochastic discount factor and I_{t+s} denotes the changes of static incomes, which can be described by:

$$I_t = \underbrace{\frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau}}_{\textit{Wealth Effect}} \underbrace{- \int_0^1 \frac{\partial}{\partial \tau}\Big[(1-\tau) r_t \Phi_i k_{i,t}\Big] di}_{\textit{MPK Wedge Loss}}$$
$$+ w_t \underbrace{\int_0^1 \Big[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\Big] \frac{\partial k_{i,t}}{\partial \tau} di}_{\textit{Automation Dispersion Loss}} + w_t \underbrace{\Big[\gamma(\bar{J}_t)^{-1} - \gamma(J_t^*)^{-1}\Big] \frac{\partial K_t^{DE}}{\partial \tau}}_{\textit{Mean-Level Automation Gain}},$$

where Mean-Level Automation Gain becomes positive if and only if $\bar{J}_t < J_t^*$, while Automation Dispersion Loss is constantly negative.

Proof. See Online Appendix C.

Proposition 2 demonstrates that the net welfare impact of the robot subsidy can be decomposed into four components: the first component represents general equilibrium wealth effect, the second component represents the change of mechanical income loss arising from borrowing costs in the form of MPK wedges. The remaining two terms, the *mean-level automation gain* and *automation dispersion loss*, are specifically related to automation. The mean-level automation gain 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-level automation gain becomes positive if and only if the mean automation level is below the socially optimal one, i.e., $\bar{J}_t < J_t^*$.

As we assume positive borrowing costs for all firms ($\Phi_i > 0$ for $\forall i$), the mean automation adoption is likely depressed, and the economy tends to benefit from a positive mean-level automation gain.

The automation dispersion loss 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 turnovers $p_{i,t}y_{i,t}$ 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.[5]

Propositions 2 underscores 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. Hence, a uniform robot subsidy τ could be welfare-improving, as it boosts firms' automation adoption and realigns aggregate factor usage to efficient levels; On the other hand, financial frictions also introduce ex-ante distortions in factor allocation and heterogeneous automation adoption across firms. That results in uneven benefits from a uniform robot subsidy, which could be further intensified by ex-post endogenous automation adoption. In summary, the aggregate welfare implication of a uniform robot subsidy relies on the relative magnitudes of these two countervailing forces. In the next step, we will quantify the aggregate

[5] While in the analysis here we focus mainly on the welfare implications of the automation dispersion, we also discuss in detail in Online Appendix C.3 how it could potentially exacerbates the static productivity loss induced by ex-ante capital misallocation. More specifically, we did a similar practice as in Hsieh and Klenow (2009) and show that endogenous automation amplifies the TFP loss through three distinct channels.

impacts by accounting for the nature of existing financial frictions in a full general equilibrium framework.

5 Full Model Quantifying Efficiency Implications of Uniform Robot Subsidy

In the full model, we 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), we argue the adoption of industrial robots could affect labor and capital income disproportionally, rendering exacerbated capital accumulation dispersion and subsequent enlarged efficiency loss from inequality (e.g., Moll et al. (2022)).

5.1 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 subject to a flow budget constraint and occupation choice:

$$\begin{aligned} V(a_{i,0}, z_{i,t}) = \max_{\{c_{i,t}\}} \quad & \int_0^\infty e^{-\varepsilon t} \log(c_{i,t}) dt, \\ \text{s.t.} \quad & \dot{a_{i,t}} = r_t a_{i,t} + \max\{w_t, \pi_{i,t} - c_f\} - T_t - c_{i,t}. \end{aligned} \tag{8}$$

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 $z_{i,t}$. We will describe the detailed expression of the profit function and the stochastic process of the entrepreneurial talent later.

We further assume that the capital accumulation is subject to dissipation shocks that arrive at a Poisson rate p. Following Moll et al. (2022), we 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 $a_{i,t} = 0$.[6] 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:

$$\begin{aligned} \epsilon V(a_{i,t}, z_{i,t}) = \max_{\{c_{i,t}\}} \ & \log(c_{i,t}) + \frac{\partial V_{i,t}}{\partial a_{i,t}} \Big[r_t a_{i,t} + \max\{w_t, \pi_{i,t} - c_f\} - T_t - c_{i,t} \Big] \\ & + \frac{\partial V_{i,t}}{\partial z_{i,t}} \mu(z_{i,t}) + \frac{1}{2} \frac{\partial^2 V_{i,t}}{\partial z_{i,t}^2} \sigma(z_{i,t})^2. \end{aligned} \tag{9}$$

Equation 9 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:

$$0 = -\frac{\partial}{\partial a}\big[s(a,z)g(a,z)\big] - \frac{\partial}{\partial z}[\mu(z)g(a,z)] + \frac{1}{2}\frac{\partial^2}{\partial z^2}[\sigma(z)^2 g(a,z)] - pg(a,z) + p\psi(a,z). \tag{10}$$

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 labor $l_{i,t}$, 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 4, entrepreneur i maximizes the profit π_i subject to endogenous au-

[6] 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).

tomation adoption and financial frictions. The dynamic framework departs from the simplified production technology in two ways: First, we endogenize the financial frictions by connecting the borrowing costs Φ_i to the asset positions of the households. we adopt the functional form proposed by David and Venkateswaran (2019):

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

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, we assume traditional capital and industrial robots are affected by identical borrowing costs.

Second, we 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 labor 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:

$$
\begin{aligned}
\pi_{i,t} = \max_{\{y_{i,t},k_{i,t},l_{i,t},m_{i,t},J_{i,t}\}} \quad & p_{i,t}y_{i,t} - w_t l_{i,t} - [(1+\Phi(a_{i,t}))r_t + \delta]k_{i,t} - [(1-\tau_t)(1+\Phi(a_{i,t}))r_t^m + \delta]m_{i,t}, \\
\text{s.t.} \quad & p_{i,t} = y_t^{\frac{1}{\sigma}} {y_{i,t}}^{-\frac{1}{\sigma}}, \\
& kl_{i,t} = k_{i,t}^{\alpha} l_{i,t}^{1-\alpha}, \\
& y_{i,t} = z_i \left\{ {J_{i,t}}^{\frac{1}{\rho}} m_{i,t}^{\frac{\rho-1}{\rho}} + \left[\int_{J_{i,t}}^{1} \gamma(x)^{\rho-1} dx \right]^{\frac{1}{\rho}} kl_{i,t}^{\frac{\rho-1}{\rho}} \right\}^{\frac{\rho}{\rho-1}\nu},
\end{aligned}
\tag{11}
$$

with $z_{i,t}$ denoting the entrepreneur's managerial talent. The logarithm of entrepreneurial talent follows an Ornstein-Uhlenbeck process with long-term mean μ_z described by:

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

where $\mu(z_{i,t}) = \theta_z[\mu_z - \log(z_{i,t})]z_{i,t} + \frac{\sigma_z^2}{2}z_{i,t}$, $\sigma(z_{i,t}) = \sigma_z z_{i,t}$, and $dW_{i,t}$ denotes the Wiener process.

A special case of Equation 11 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, we will rely on this special case to distinguish parameters governing the tradition and automation technologies.

Robotics Industry

Since the robotics industry itself is not the focus of this study, we impose limited structure on the robotics industry and assume traditional capital k_t can be converted into industrial robots M_t with productivity z_t^m:

$$
\begin{aligned}
\max_{\{M_t,k_t^m\}} \quad & r_t^m M_t - r_t k_t^m, \\
\text{s.t.} \quad & M_t = z_t^m k_t^m.
\end{aligned}
\tag{12}
$$

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 follows:

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

Market Clearing

Wage rate w_t, industry robot rental rate r_t^m and interest rate r_t clear the labor, industrial robot and capital market respectively:

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

$$\int_{i\in\Omega_t} m_{i,t} di = M_t, \tag{15}$$

$$\int_{i\in\Omega_t} k_{i,t} di + k_t^m = \int_0^1 a_{i,t} di. \tag{16}$$

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

$$\left[\int_{i\in\Omega_t} p_{i,t}^{1-\sigma} di\right]^{\frac{1}{1-\sigma}} = 1. \tag{17}$$

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 $J(a,z)$, outputs and factor demands, $y(a,z)$, $k(a,z)$, $l(a,z)$ and $m(a,z)$, robotics industry supply and factor demand M and k^m,the government's lump-sum tax T, and prices w, r^m, r, $p(a,z)$ such that, given a uniform robot subsidy τ:

1. $c(a,z)$ and Ω satisfy the households' HJB equation 9;
2. $g(a,z)$ satisfies the Kolmogorov Forward equation 10;

3. $J(a,z)$, $y(a,z)$, $k(a,z)$, $l(a,z)$ and $m(a,z)$ satisfy the firms' profit maximization problem 11;

4. M and k^m satisfy the robotics industry profit maximization problem 12;

5. w, r^m and r satisfy the factor market clearing conditions 14, 15 and 23, and $p(a,z)$ satisfies the one-price principle 17;

6. T satisfies the government budget balance condition 13.

5.2 Calibration

Our benchmark model is calibrated to match productivity dispersion, firm size and financial frictions of China's industrial sector in 2010. We then calibrate the task-based technology to capture the industrial robot density in 2010 and 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 4 presents the calibration targets. See Online Appendix D for more details.

For households preferences, we adopt a standard value for the elasticity of substitution across varieties $\sigma = 7$. We 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), we set the yearly dissipation rate, p, to achieve a capital supply elasticity $d\log(K)/dr \approx 25$.

Turning to the production technology, we set the labor input elasticity in producing capital service $\alpha = 0.6$ to match China's 2010 labor income share when industrial robot usage was minimal. We adopt a standard value for capital depreciation rate, $\delta = 0.05$, and for the span-of-control parameter, $\nu = 0.85$ [7]. 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 tal-

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

ents) of entrepreneurs, we 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.

To bring the task-based technology to data, we 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.

We 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-labor ratio of 0.003, corresponding to a density of around 30 industrial robots per 10,000 manufacturing workers in the manufacturing 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, we follow the approach suggested by David and Venkateswaran (2019). More specifically, firms' maximization problem 11 implies:[8]

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

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

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

Table 4: 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 - labor 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 = 3.5
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 49.58%

regression:

$$\log(\frac{k_i}{wl_i}) = \gamma_1 + \log(1 + \gamma_2 + a_i^{\omega}) + \mu_s + \epsilon_i. \tag{18}$$

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. γ_1 and γ_2 are constants. We 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. We calibrate the financial frictions scalar β to match the average scale of the capital usage restrictions.

5.3 Link to Empirical Findings

In order to study the impacts of the industrial robot subsidy implemented by the Chinese local governments, we 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, we 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 5 illustrates the percentage change for specific aggregates, relative to the benchmark scenario, given different magnitudes of robot subsidy. Our analysis reveals that the robot subsidy significantly promotes industrial robot demand and positively impacts overall output. Specifically, Panel A of Table 5 shows that a robot subsidy of 20% results in a substantial 65.3% increase in industrial robot demand and an overall output growth of 1.2%. 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 1.3% 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 5 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 (5.3%), capital expenditure (22.7%) and profits (6.8%). In contrast, the bottom 50% of entrepreneurs suffer from shrinking market share and profits, with turnover and profits decreasing by 1.7% and 1.2%, respectively.[9]

An important observation is that top firms significantly increase their labor demand following a subsidy, while bottom firms experience a reduction in employment. Under a 20% subsidy, employment in top firms rises by 2.9%, whereas bottom firms see a decrease of 0.9%. This suggests that the reduction in overall labor demand due to automation primarily occurs at the extensive margin,

[9]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 5: 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.

where large firms crowd out smaller ones. Consequently, while top firms expand and absorb more labor, smaller firms face increased competitive pressure, leading to shrinking labor 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 11.9%, which is around double the improvement in average asset position of the bottom 50% of entrepreneurs (5.7%). 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.

5.4 Productivity Discussion

In this subsection, we 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.[10] As described in Section 4, the effect of a subsidy can be decomposed into the *mean-level automation gain* and the *automation dispersion loss*. The mean of automation in Panel A of Table 6 measures the ratio of dispersion-purged automation to the socially optimal level in each scenario, which captures the mean-level automation gain. 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 36% of the optimal level. Column 6 of Table 6 shows that a 20% subsidy improves the mean automation of the economy by around 22 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 6 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 loss. 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 1.2% under the 20% scenario, but a decline in TFP of 2.4%. This decline in TFP highlights the productivity loss introduced by increased dispersion. We further measure the social welfare using a utilitarian approach with equal weights. Our analysis shows that, on the basis of our current calibration of the existing financial

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

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 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 level.

In this section with the full model, we differ from the analysis in Section 4, as we 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 6, 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 labor 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, we conduct a static counterfactual analysis for each subsidy scenario. In this exercise, we substitute the distribution of households $g(a, z)$ with the one from the benchmark framework, while keeping aggregate factor demands constant. We 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 6. By shutting down the dynamic mechanism, we effectively reduce the growth in capital returns and in entrepreneurial profits along with smaller 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. Our 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 37% higher without the dynamic distortion.

Table 6: 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.

5.5 Extension to Include Spatial Structure

In this subsection, we embed the mechanism into a simple spatial structure, so as to explore the spatial spillover and misallocation caused by the municipal-level robot subsidy. Due to technical constraint as a spatial framework scales up the number of state variables exponentially, we do not calibrate a full spatial model of 286 municipalities. Instead, we apply the same sets of parameters in the previous section to two identical municipalities as in the benchmark case. Then we feed a robot subsidy to one municipality to test the aggregate impacts of such policy. More specifically, we assume that there are two municipalities c_1 and c_2, where one unit mass of households in each

municipality maximizes life-time utility subject to local flow budget constraints:[11]

$$\begin{aligned} V(a_{ic,0}, z_{ic,t}) = \max_{\{c_{ic,t}\}} \quad & \int_0^\infty e^{-\varepsilon t} \log(c_{ic,t}) dt, \\ \text{s.t.} \quad & P_{c,t} \dot{a_{ic,t}} = r_t a_{ic,t} + \max\{w_{c,t}, \pi_{ic,t} - P_{c,t} c_f\} - T^H_{c,t} - P_{c,t} c_{ic,t}. \end{aligned} \tag{19}$$

On the production side, firm i in municipality c produces and supplies its variety subject to iceberg cost $\eta_{cc'} \geq 1$. Denote the quantity of such variety as $y_{icc',t}$, then different varieties aggregate to a local final good $Y_{c,t}$ in a CES way with elasticity $\sigma > 1$:

$$Y_{c,t} = \left[\sum_{c'=c_1,c_2} \int_{i \in \Omega_{c',t}} y_{ic'c,t}^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}. \tag{20}$$

The economy satisfies three sets of market clearing conditions. Local wage rates $w_{c,t}$ clear local labor markets:

$$\int_{i \in \Omega_{c,t}} l_{ic,t} di = 1 - |\Omega_{c,t}|. \tag{21}$$

Industry robot rental rate r^m_t and interest rate r_t clear the national industrial robot and capital market respectively:

$$\sum_{c=c_1,c_2} \int_{i \in \Omega_{c,t}} m_{ic,t} di = M_t, \tag{22}$$

$$\sum_{c=c_1,c_2} \int_{i \in \Omega_{c,t}} k_{ic,t} di + k^m_t = \sum_{c=c_1,c_2} \int_0^1 a_{ic,t} di. \tag{23}$$

Panels A and B of Table 7 show the impacts of robot subsidies on the targeted and spillover municipalities, respectively. The results for the targeted municipality mirror those in the benchmark model: subsidies increase robot adoption, intensify firm dispersion by enhancing turnover of top entrepreneurs while reducing the total number of firms, as well as enlarge labor and capital

[11] Here, we abstract from the households' migration decisions and assume that there is a fixed unit mass households in each municipality.

Table 7: Changes of Numbers and Financial Performances of Firms in Robot Subsidy

Robot Subsidy τ	5%	10%	20%	30%
Panel A: Aggregates - Targeted City				
Industrial Robot Demand	15.50%	33.96%	82.30%	150.86%
Number of Firms	-0.36%	-0.43%	-1.20%	-2.42%
Turnover (Top 10%)	0.55%	1.36%	2.96%	4.79%
Turnover (Bottom 50%)	0.21%	-0.16%	-0.61%	-1.95%
Wage	-0.25%	-0.57%	-1.50%	-3.07%
Interest Rate	0.66%	1.46%	3.64%	6.99%
Average Profit	0.99%	1.79%	4.23%	7.39%
Panel B: Aggregates - Spillover City				
Industrial Robot Demand	-2.21%	-4.83%	-11.55%	-20.69%
Number of Firms	-0.37%	-0.40%	-0.92%	-1.49%
Turnover (Top 10%)	-0.28%	-0.37%	-0.88%	-1.50%
Turnover (Bottom 50%)	0.23%	-0.10%	-0.37%	-1.04%
Wage	-0.03%	-0.06%	-0.17%	-0.35%
Interest Rate	0.66%	1.46%	3.64%	6.99%
Average Profit	0.23%	0.23%	0.26%	0.26%
Panel C: Efficiency - Targeted City				
Mean of Automation	42.93%	51.27%	75.10%	114.59%
STD of Automation	16.03%	35.30%	85.49%	155.68%
Output	0.32%	0.65%	1.26%	1.59%
TFP	-0.06%	-0.18%	-0.48%	-0.88%
Welfare	-0.40%	-1.09%	-4.08%	-10.95%
Panel D: Efficiency - Spillover City				
Mean of Automation	36.34%	36.41%	36.38%	35.99%
STD of Automation	-1.63%	-3.59%	-9.17%	-17.35%
Output	-0.01%	0.00%	0.01%	0.09%
TFP	-0.03%	-0.07%	-0.06%	0.10%
Welfare	0.52%	1.20%	3.11%	6.29%

Note: (1) Without further specification, values represent percentage changes of outcomes relative to the benchmark model in response to 5%, 10%, 20% and 30% robot subsidy respectively; (2) 'Turnover (Top 10%)' and 'Turnover (Bottom 50%)' describe the average turnovers of entrepreneurs with top 10% turnover and bottom 50% turnover respectively; (3) The 'Mean of Automation' row measures the deviation of dispersion-purged automation from the socially-optimal automation in different scenarios; (4) 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; (5) The 'Welfare' row is calculated with the Utilitarian approach.

income differences. In the spillover municipality, however, the subsidy induces negative externalities. Higher national interest rates crowd out local robot adoption. Increased competition from the subsidized region reduces the number of entrepreneurs and depresses turnover of firms across the whole distribution. Meanwhile, labor-capital income divergence also occurs in the spillover municipality, which exacerbates capital accumulation dispersion.

Panels C and D summarize the efficiency and welfare implications of the robot subsidy in the

targeted and spillover cities, respectively. In line with the benchmark results, the targeted city experiences a rise in average automation but also a sharp increase in automation dispersion, which reduces both TFP and welfare. Notably, in the presence of trade, the welfare cost of this dispersion becomes more pronounced, as top firms are able to better exploit their productivity advantages with larger market access.

In contrast, Panel D shows that although robot adoption declines in the spillover city, automation dispersion also narrows, as fewer firms invest in robots and the response becomes more homogeneous. As a result, as the intensity of robot subsidy increases, the TFP of the spillover municipality first drops then rebounds. The output also follows a similar trend. In addition to the improvement of allocative efficiency within the city, trading with the more automated and subsidized region also results in falling local price levels. Therefore, the aggregate welfare in the spillover city improves. The finding points out that, while introducing robot subsidy in the neighboring municipality might crowds out local firms, the aggregate welfare impacts could be positive.

6 Conclusions

This study examines the impact of China's robot subsidy policies on manufacturing, focusing on demand-side subsidies that encourage firms to adopt robots. Using a difference-in-differences design on municipal-level data, we find that the benefits of the uniform robot subsidy are uneven across firms - while large firms grow, new firm entry declines, which indicates that subsidies may distort competition and exacerbate firm inequality.

To explain these patterns, we develop a task-based model with capital misallocation. Subsidies introduce a trade-off by raising average automation but also widening automation dispersion. When embedded into a dynamic heterogeneous-agent model, we find that a 20% subsidy boosts robot demand by 65% and output by 1.23%, but lowers TFP by 2.40%. Welfare gains exist for mod-

erate subsidies (less than 10%) but turn negative beyond 20%, as dispersion-driven misallocation dominates.

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A Supplementary Materials of Research Background

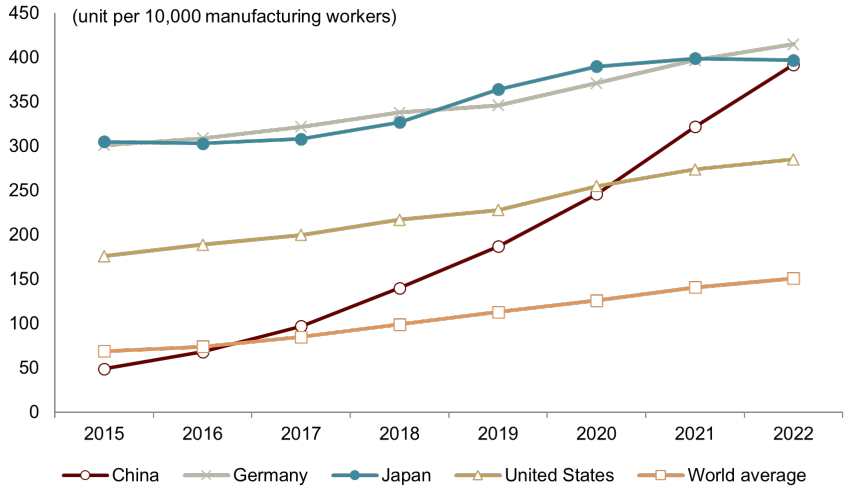


Figure A1: Number of Municipalities That Introduced Robot Demand-Side Subsidy

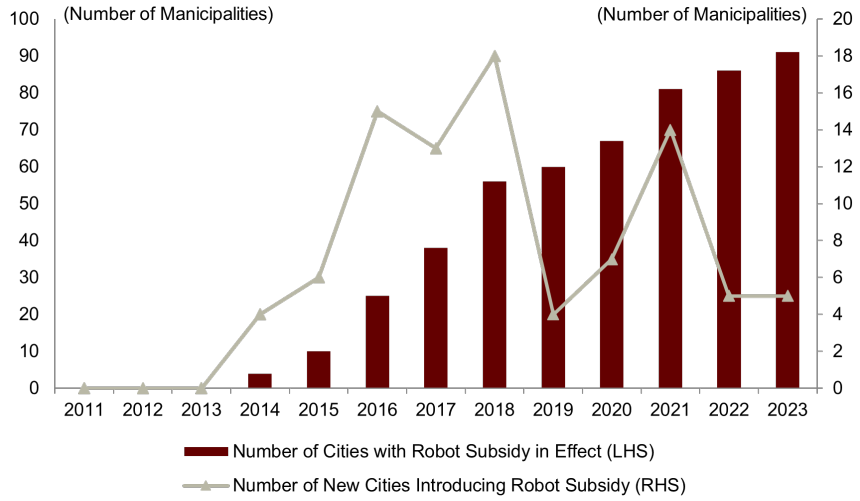


Figure A2: Number of Municipalities That Introduced Robot Demand-Side Subsidy

Table A1: 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).

B Supplementary Materials of Empirical

B.1 Data

B.1.1 Text Recognition

At the local level, we need to categorize and identify specific industrial policies on industrial robot deployment with concrete and executable subsidization measures. To pinpoint the relevant policies, we use data from the PKULaw dataset of laws and regulations. This resource comprehensively documents laws, regulations and administrative documents issued by both central and local governments in China since 1949. Leveraging this dataset enables us to identify local government policies that offer subsidies for robots.

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. We extract the original texts of the policies, which make up the specifics of each regulation. Using an automatic text-recognition algorithm that

examines each policy's complete text, we categorize the policies by type, specifically concentrating on those that offer direct financial subsidies to manufacturing enterprises for purchasing industrial robots.

A policy is identified 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. Specifically, we use the following Chinese keywords: "机器人", "自动化", "智能设备", "智能装备", "智能装置", "智能化设备", "智能化装备" and "智能化装置".

- Second, it must outline a detailed and executable subsidy scheme that includes the description of a specific amount of money, allowing for the verification of the extent of financial assistance provided for each acquisition or lease. To achieve this, we use a combination of number with money-related Chinese keywords: "万元", "亿元" and "%".

- Finally, the document must explicitly state that the financial assistance is a subsidy, enabling us to classify it as a subsidy policy. To achieve this goal, we include a set of subsidy-related Chinese keywords in our identification process: "补贴", "补助", "津贴", "奖励", "奖金", "资助", "赞助", "贴息", "减免", "资金", "扶持" and "奖补".

This approach allows us to confine the study to municipal-level robot-related industrial policies with explicit subsidy measures. Then, we manually check each document to filter out policies that, while satisfying the above criteria, weren't genuinely focused on robots. The following policy provides an example of a robot subsidy policy issued by the government of Guangzhou City in 2014:



Figure B3: An Example of Municipal-Level Robot Subsidy

B.1.2 Descriptive Evidence on Municipal-level Robot Subsidies

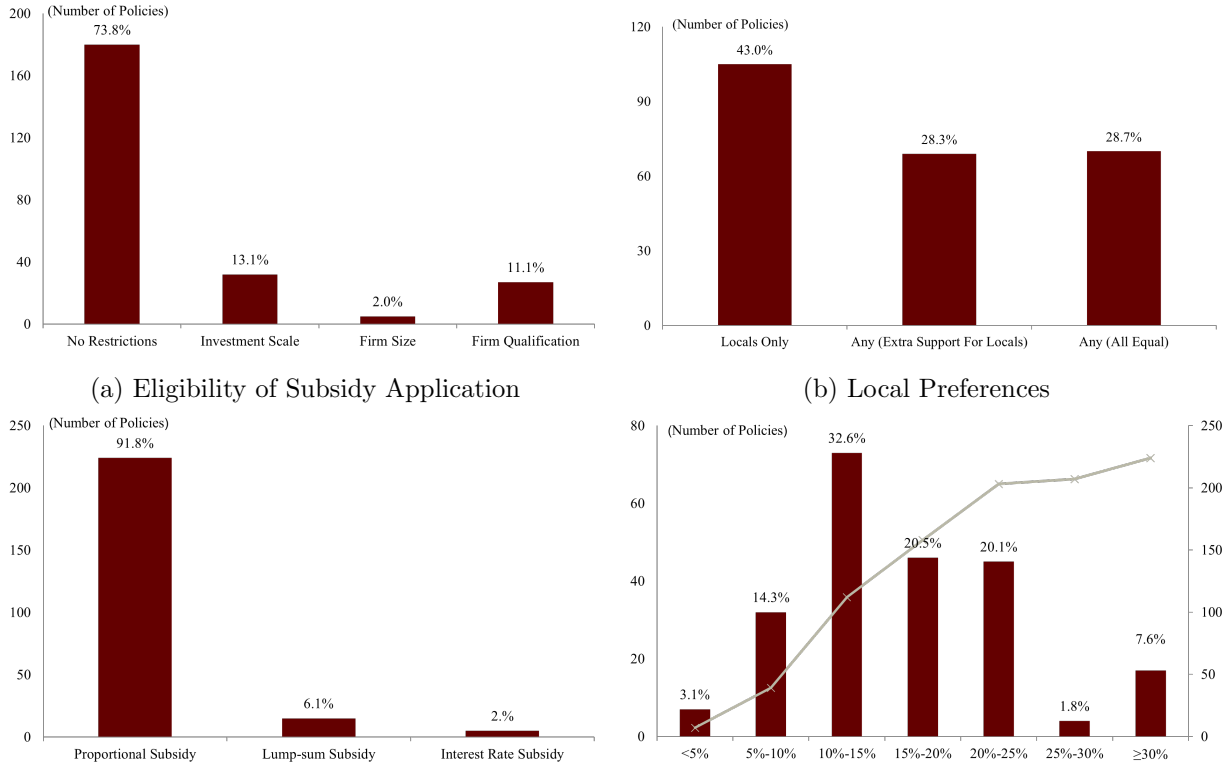
We identify 244 municipal-level robot subsidy policies issued between 2014 and 2023. These policies exhibit three key features:

- **Non-Exclusiveness:** The majority of municipal-level subsidies are non-exclusive. As shown in Panel (a) of Figure B4, a dominant share of the policies (73.8%) imposes no restriction on the eligibility of applicants. An additional 13.1% of policies require only that the applicant's investment in industrial robots surpass a specified threshold. Beyond these, only 2% impose requirements on firm size, such as minimum turnover or number of employees. Around 11.1% mandate that applicants hold specific government-recognized qualifications (e.g., designation as a high-tech enterprise or smart factory). Overall, most subsidies can be regarded as uniform across firms.

- **Local Preferences:** The subsidies display a strong bias toward supporting local manufacturers. As shown in Panel (b) of Figure B4, approximately 43% of policies exclusively subsidize robot equipment produced by local firms, while 28.3% offer support to all firms but provide

additional subsidies for equipment from local producers. Only 28.7% of the policies treat all producers equally, indicating the presence of substantial local protectionism in municipal-level robot subsidy implementation.

- **Subsidy Method and Intensity:** Most subsidies (91.8%) are implemented as proportional price discounts on industrial robot equipment. Among the 224 proportional subsidy policies, Panel (d) of Figure B4 illustrates the distribution of subsidy rates. Roughly 50% of the policies offer a subsidy rate exceeding 15%, and the average subsidy rate across all policies is approximately 17.5%.



(a) Eligibility of Subsidy Application

(b) Local Preferences

(c) Method of Subsidy

(d) Subsidy Ratio

Figure B4: Descriptive Evidence on Municipal-Level Robot Subsidies

B.1.3 Identifying Robotic Patents

We identify robotic patents from the full set of patent applications obtained from China National Intellectual Property Administration. More specifically, we identify the patents related to robotics technology and classify them into two categories:

- **Robot Unit Patent:** Patents with titles or descriptions that include any of the following industrial robot whole unit keywords in Chinese: "机器人", "机械臂", "机械手", "AGV", "自动导向", "自动化导向", "自动引导", "自动化引导", "自动导引" and "自动化导引".

- **Robot Module Patent:** Patents with titles or descriptions that include any of the following industrial robot module keywords in Chinese: "伺服马达", "伺服电机", "减速器" and "减速机".

B.2 Robustness Checks

Figures B5 - B10 present the results of the analysis on outcomes of interest using various DID methods. While we assert that SDID (Arkhangelsky et al. 2021) is the most appropriate for our empirical setting, we 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 2 and 3. This consistency suggests that our 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 our OLS results, which suggest that the introduction of robot subsidy policies may be endogenous to observable

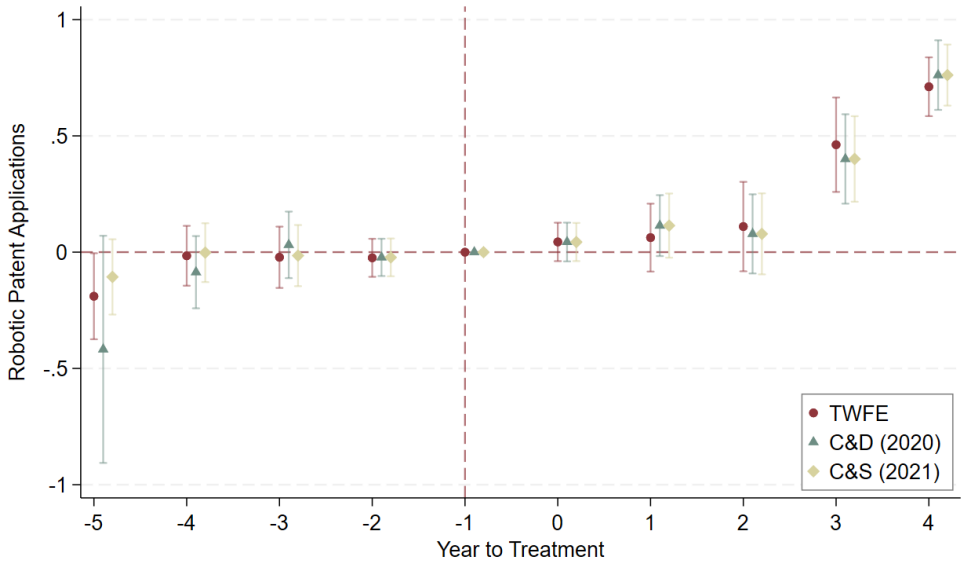


Figure B5: Event Study Robustness Check - Robotics Patent Applications

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.

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 our 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.

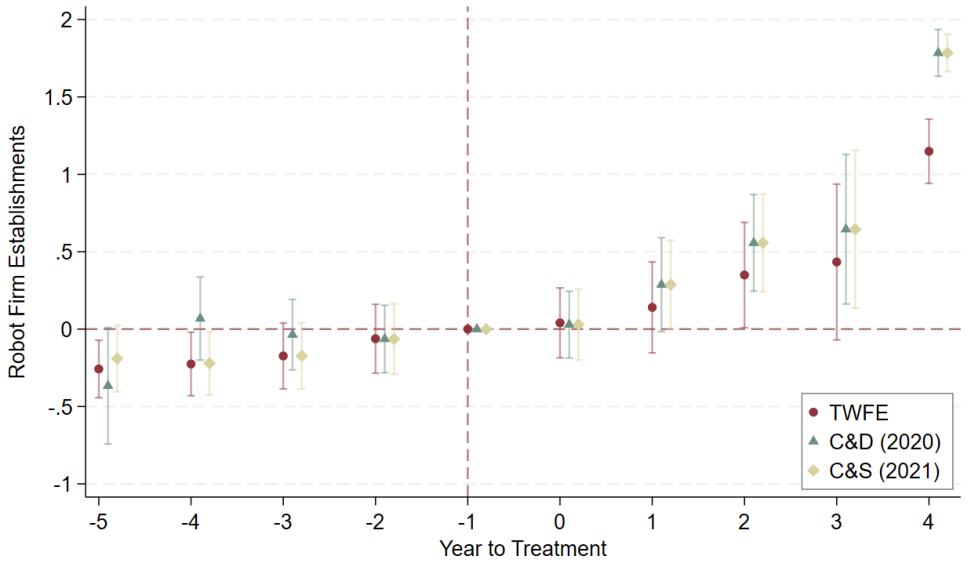


Figure B6: Event Study Robustness Check - Robot Firm Establishments

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.

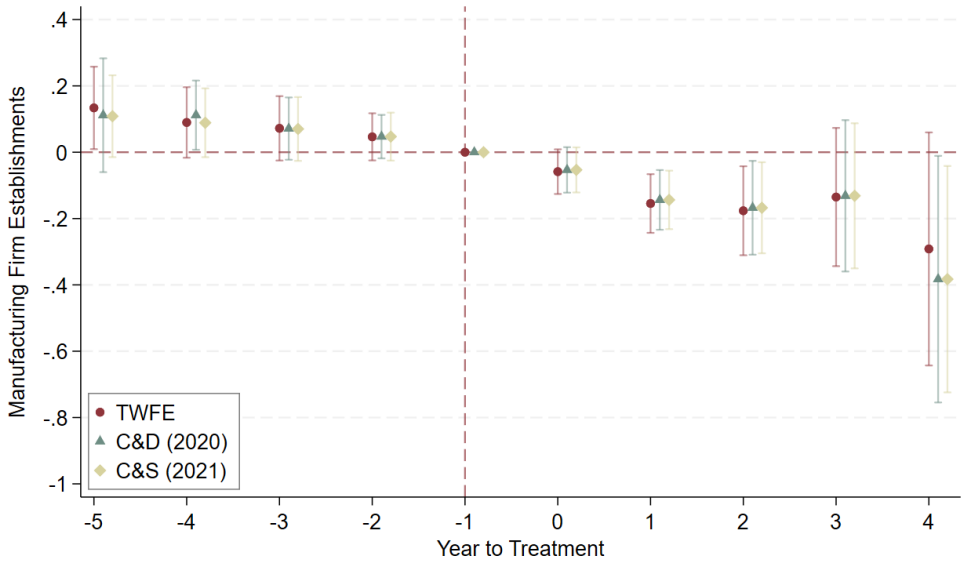


Figure B7: Event Study Robustness Check - Manufacturing Firm Establishments

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.

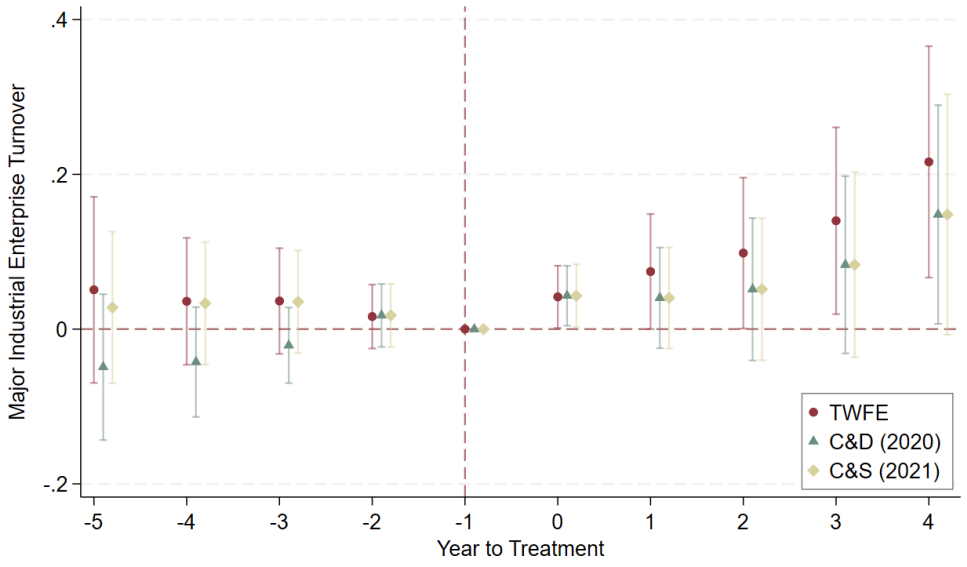


Figure B8: Event Study Robustness Check - Major Industrial Enterprise Turnover

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.

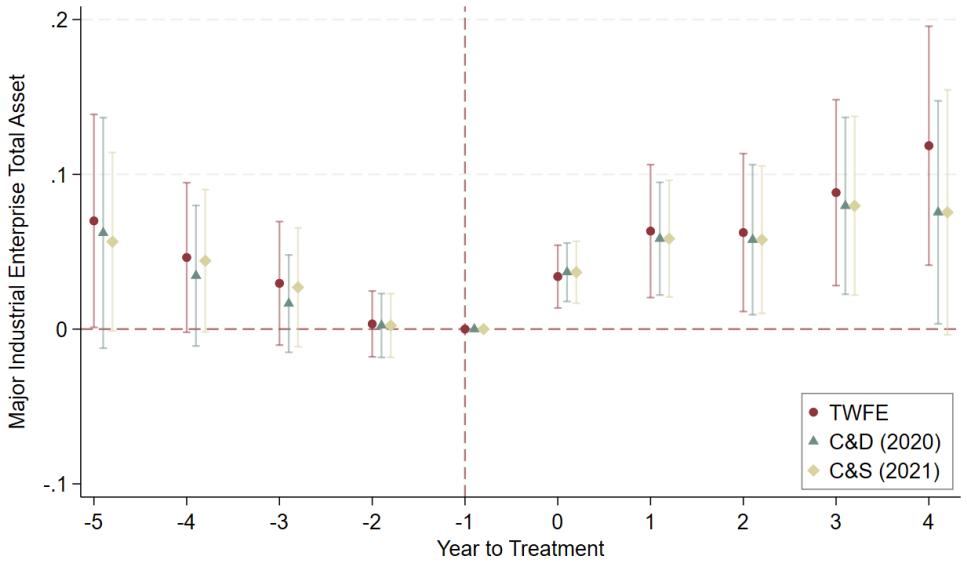


Figure B9: Event Study Robustness Check - Major Industrial Enterprise Total Asset

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.

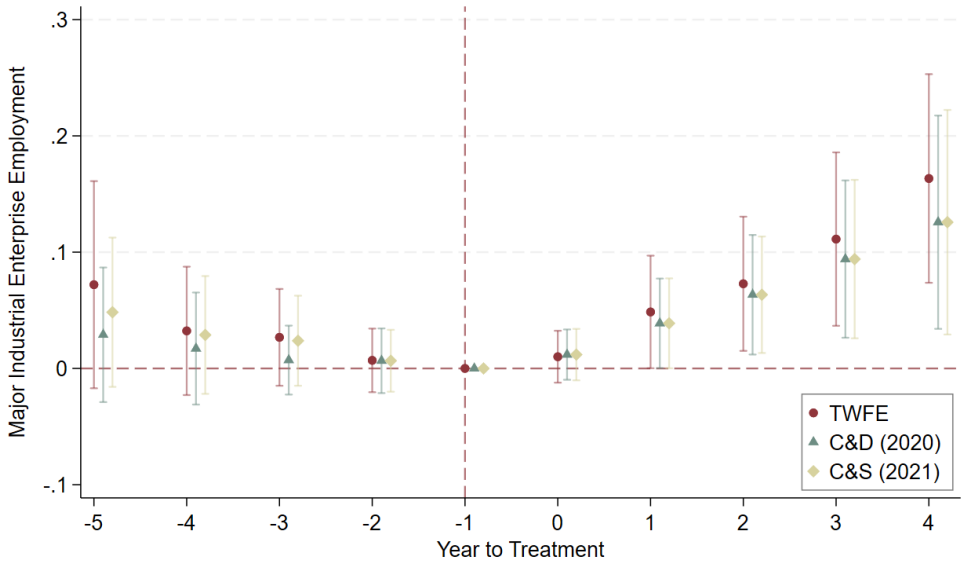


Figure B10: Event Study Robustness Check - Major Industrial Enterprise Employment

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.

B.3 Additional Results

B.3.1 Descriptive Statistics

Table B2: 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.

B.3.2 Selection Criteria

Table B3: 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.

C Simplified Model Appendix

C.1 Equilibrium Definition

The general equilibrium of the model consists of firms' automation levels $J_{i,t}$, factor demands $l_{i,t}$ and $k_{i,t}$, prices $mc_{i,t}$ and $p_{i,t}$, outputs $y_{i,t}$, and profits $\pi_{i,t}$, representative household's consumption c_t and asset position a_{t+1}, aggregate factor prices w_t, r_t and output y_t, and government lump-sum tax T_t, such that they satisfy the following set of first-order conditions:

$$
\begin{cases}
mc_{i,t} = \dfrac{1}{z_{i,t}}\left[[(1-\tau)(1+\Phi_i)r_t]^{1-\rho}J_{i,t} + w_t^{1-\rho}\displaystyle\int_{J_{i,t}}^{1}\gamma(x)^{\rho-1}dx\right]^{\frac{1}{1-\rho}}, \\
p_{i,t} = \dfrac{\sigma}{\sigma-1}mc_{i,t}, \\
y_{i,t} = y_t p_{i,t}^{-\sigma}, \\
l_{i,t} = \left[\dfrac{mc_{i,t}}{w_t}\right]^{\rho} z_{i,t}^{\rho-1}\left(\displaystyle\int_{J_{i,t}}^{1}\gamma(x)^{\rho-1}dx\right)y_{i,t}, \\
k_{i,t} = \left[\dfrac{mc_{i,t}}{(1-\tau)(1+\Phi_i)r_t}\right]^{\rho} z_{i,t}^{\rho-1}J_{i,t}y_{i,t}, \\
\gamma(J_{i,t}) = \dfrac{w_t}{(1-\tau)(1+\Phi_i)r_t}, \\
\pi_{i,t} = p_{i,t}y_{i,t} - (1-\tau)(1+\Phi_i)r_t k_{i,t} - w_t l_{i,t}, \\
u'(c_{t+1}) = \beta(1+r_t)u'(c_t), \\
c_t + a_{t+1} = w_t + (1+r_t)a_t + \displaystyle\int_0^1 \pi_{i,t}di - T_t, \\
T_t = \tau r_t \displaystyle\int_0^1 k_{i,t}di, \\
\displaystyle\int_0^1 k_{i,t}di = a_t, \\
\displaystyle\int_0^1 l_{i,t}di = 1, \\
y_t = \left[\displaystyle\int_0^1 y_{i,t}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.
\end{cases}
\tag{24}
$$

C.2 Proofs

Lemma 1: Proof. Consider a production side optimization problem with fixed factor prices r and w. The steady-state automation level and marginal cost of firm i can be described by:

$$\gamma(J_i) = \frac{w}{(1-\tau)(1+\Phi_i)r}, \tag{25}$$

$$mc_i = \frac{1}{z_i}\left[[(1-\tau)(1+\Phi_i)r]^{1-\rho}J_i + w^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx\right]^{\frac{1}{1-\rho}}. \tag{26}$$

Equation 26 yields that, provided fixed factor prices r and w, a marginal increase in the robot subsidy τ leads to the following change of marginal cost mc_i:

$$\begin{aligned}
\frac{\partial \log(mc_i)}{\partial \tau} &= \frac{\partial}{\partial \tau}\left\{ -\log z_i + \frac{1}{1-\rho}\log\left[[(1-\tau)(1+\Phi_i)r]^{1-\rho}J_i + w^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx\right]\right\}, \\
&= \frac{1}{1-\rho}\frac{-(1-\rho)[(1-\tau)(1+\Phi_i)r]^{-\rho}(1+\Phi_i)rJ_i + [(1-\tau)(1+\Phi_i)r]^{1-\rho}\frac{\partial J_i}{\partial \tau} - w^{1-\rho}\gamma(J_i)^{\rho-1}\frac{\partial J_i}{\partial \tau}}{[(1-\tau)(1+\Phi_i)r]^{1-\rho}J_i + w^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}, \\
&= -\frac{[(1-\tau)(1+\Phi_i)r]^{-\rho}(1+\Phi_i)rJ_i}{[(1-\tau)(1+\Phi_i)r]^{1-\rho}J_i + w^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}, \\
&= -\frac{J_i}{J_i + \left[\frac{w}{(1-\tau)(1+\Phi_i)r}\right]^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}\frac{(1+\Phi_i)r}{(1-\tau)(1+\Phi_i)r}, \\
&= -\frac{J_i}{J_i + \gamma(J_i)^{1-\rho}\int_{J_i}^{1}\gamma(x)^{\rho-1}dx}\frac{1}{1-\tau}.
\end{aligned}$$

Next, we will show that the reduction of the marginal cost is decreasing in borrowing cost Φ_i. Denote $\frac{\partial \log mc}{\partial \tau}$ as a function of Φ as follows:

$$\begin{aligned}
\frac{\partial \log mc}{\partial \tau} &= -\frac{J}{J + \gamma(J)^{1-\rho}\int_{J}^{1}\gamma(x)^{\rho-1}dx}\frac{1}{1-\tau}, \\
&= -\frac{1}{1 + J^{-1}\gamma(J)^{1-\rho}\int_{J}^{1}\gamma(x)^{\rho-1}dx}\frac{1}{1-\tau}.
\end{aligned} \tag{27}$$

Since $\gamma(J)^{-1}$, J^{-1}, $\gamma(J)^{-\rho}$ and $\int_J^1\gamma(x)^{\rho-1}dx$ are all monotonically decreasing in J, while Equation 25 implies that J is decreasing in Φ, hence $\frac{\partial \log mc}{\partial \tau}$ is monotonically increasing in Φ: $\frac{\partial^2 \log mc}{\partial \tau \partial \Phi} > 0$.

■

Proposition 1: Proof. Consider a production side optimization problem with fixed factor prices r and w, the steady-state turnover of firm i can be described by:

$$\begin{aligned} p_i y_i &= py \frac{p_{i,t}}{p_t}^{1-\sigma}, \\ &= py \frac{mc_i^{1-\sigma}}{\int_0^1 mc_x^{1-\sigma} dx}. \end{aligned}$$

Assume that the wealth effect is sufficiently small $\frac{\partial py}{\partial \tau} \approx 0$, then the change of the turnover can be described by:

$$\begin{aligned} \frac{\partial p_i y_i}{\partial \tau} &= py \frac{\int_0^1 mc_x^{1-\sigma} dx \cdot \frac{\partial}{\partial \tau}\{mc_i^{1-\sigma}\} - mc_i^{1-\sigma} \cdot \frac{\partial}{\partial \tau}\{\int_0^1 mc_x^{1-\sigma} dx\}}{\left(\int_0^1 mc_x^{1-\sigma} dx\right)^2}, \\ &= py \frac{(1-\sigma) mc_i^{1-\sigma} \int_0^1 mc_x^{1-\sigma} dx \cdot \frac{\partial \log mc_i}{\partial \tau} - (1-\sigma) mc_i^{1-\sigma} \int_0^1 mc_x^{1-\sigma} \frac{\partial \log mc_x}{\partial \tau} dx}{\left(\int_0^1 mc_x^{1-\sigma} dx\right)^2}, \\ &= py \frac{(1-\sigma) mc_i^{1-\sigma}}{\int_0^1 mc_x^{1-\sigma} dx} \left[\frac{\partial \log mc_i}{\partial \tau} - \int_0^1 \frac{mc_x^{1-\sigma}}{\int_0^1 mc_x^{1-\sigma} dx} \frac{\partial \log mc_x}{\partial \tau} dx\right], \\ &= (1-\sigma) p_i y_i \left[\frac{\partial \log mc_i}{\partial \tau} - \int_0^1 \frac{\partial \log mc_x}{\partial \tau} \cdot share_x \, dx\right], \end{aligned}$$

where $share_x = \frac{p_i y_i}{py} \in [0,1]$ represents the market share of firm x and $\int_0^1 share_x \, dx = 1$. As shown in Lemma 1, $\frac{\partial \log mc}{\partial \tau}$ is monotonically increasing in Φ. Hence,

$$\begin{cases} \left.\frac{\partial \log mc}{\partial \tau}\right|_{\Phi=\Phi_{max}} \geq \int_0^1 \frac{\partial \log mc_x}{\partial \tau} \cdot share_x \, dx, \\ \left.\frac{\partial \log mc}{\partial \tau}\right|_{\Phi=\Phi_{min}} \leq \int_0^1 \frac{\partial \log mc_x}{\partial \tau} \cdot share_x \, dx. \end{cases}$$

Hence, there always exists $\bar{\Phi} \in [\Phi_{min}, \Phi_{max}]$ such that

$$\left.\frac{\partial \log mc}{\partial \tau}\right|_{\Phi=\bar{\Phi}} = \int_0^1 \frac{\partial \log mc_x}{\partial \tau} \cdot share_x \, dx. \tag{28}$$

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

Similarly, we can express the profits of firm i as a fixed shared of the turnover $\pi_i = \frac{1}{\sigma} p_i y_i$. Hence it follows directly that $\frac{\partial \pi_i}{\partial \tau} > 0$ if and only if $\Phi_i < \bar{\Phi}$. ■

Proposition 2: Proof. Household's problem 2 can be expressed as the following Bellman equation:

$$\begin{aligned} V(a_t, \{\Phi_i\}_{i\in[0,1]}, \tau) = \max_{\{c_t, a_{t+1}\}} & u(c_t) + \beta V(a_{t+1}, \{\Phi_i\}_{i\in[0,1]}, \tau), \\ \text{s.t. } & c_t + a_{t+1} = w_t + (1+r_t)a_t + \int_0^1 \pi_{i,t} di - T_t. \end{aligned} \tag{29}$$

Using the envelope theorem, the marginal change of the representative household's value function in a marginal rise of robot subsidy τ can be described by:

$$\begin{aligned} \frac{\partial V_t}{\partial \tau} &= \beta \frac{\partial V_{t+1}}{\partial \tau} + \lambda_t \left\{ \frac{\partial w_t}{\partial \tau} + \frac{\partial r_t}{\partial \tau} a_t + \int_0^1 \frac{\partial \pi_{i,t}}{\partial \tau} di - \frac{\partial T_t}{\partial \tau} \right\}, \\ &= \sum_{s=0}^{\infty} \beta^s \lambda_{t+s} I_{t+s}, \end{aligned}$$

where $I_t = \frac{\partial w_t}{\partial \tau} + \frac{\partial r_t}{\partial \tau} a_t + \int_0^1 \frac{\partial \pi_{i,t}}{\partial \tau} di - \frac{\partial T_t}{\partial \tau}$ desribes the change of period-by-period income, and $\lambda_t = u'(c_t)$ denotes the Lagrangian multiplier of the budget constraint. Firms' profit maximization problem 3 can be expressed by:[12]

$$\begin{aligned} \pi_{i,t} = \max_{\{y_{i,t}, k_{i,t}, l_{i,t}, J_{i,t}\}} & \; Y_t^{\frac{1}{\sigma}} y_{i,t}^{\frac{\sigma-1}{\sigma}} - w_t l_{i,t} - (1-\tau)(1+\Phi_i) r_t k_{i,t}, \\ \text{s.t.} & \quad y_{i,t} = z_{i,t} e^{\int_{J_{i,t}}^1 \log \gamma(x) dx} \left(\frac{k_{i,t}}{J_{i,t}} \right)^{J_{i,t}} \left(\frac{l_{i,t}}{1 - J_{i,t}} \right)^{1-J_{i,t}}. \end{aligned} \tag{30}$$

Using the envelope theorem, the marginal change of the profit function with respect to a marginal rise of the robot subsidy τ can be described by:

$$\begin{aligned} \int_0^1 \frac{\partial \pi_{i,t}}{\partial \tau} di &= \int_0^1 \left\{ \frac{1}{\sigma} Y_t^{\frac{1-\sigma}{\sigma}} y_{i,t}^{\frac{\sigma-1}{\sigma}} \frac{\partial Y_t}{\partial \tau} - \frac{\partial w_t}{\partial \tau} l_{i,t} + (1+\Phi_i) r_t k_{i,t} - (1-\tau)(1+\Phi_i) \frac{\partial r_t}{\partial \tau} k_{i,t} \right\} di, \\ &= \frac{1}{\sigma} \frac{\partial Y_t}{\partial \tau} - \frac{\partial w_t}{\partial \tau} \int_0^1 l_{i,t} di + r_t \int_0^1 (1+\Phi_i) k_{i,t} di - (1-\tau) \frac{\partial r_t}{\partial \tau} \int_0^1 (1+\Phi_i) k_{i,t} di. \end{aligned}$$

[12] Here we assume $\rho = 1$ for mathematical tractability.

Hence, the period-by-period income change can be expressed by:

$$\begin{aligned}
I_t &= \frac{\partial w_t}{\partial \tau} + \frac{\partial r_t}{\partial \tau} a_t + \frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau} - \frac{\partial w_t}{\partial \tau}\int_0^1 l_{i,t} di + r_t \int_0^1 (1+\Phi_i) k_{i,t} di - (1-\tau)\frac{\partial r_t}{\partial \tau}\int_0^1 (1+\Phi_i) k_{i,t} di \\
&\quad - r_t \int_0^1 k_{i,t} di - \tau \frac{\partial r_t}{\partial \tau}\int_0^1 k_{i,t} di - \tau r_t \int_0^1 \frac{\partial k_{i,t}}{\partial \tau} di, \\
&= \frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau} + \left[r_t - (1-\tau)\frac{\partial r_t}{\partial \tau}\right]\int_0^1 \Phi_i k_{i,t} di - \tau r_t \int_0^1 \frac{\partial k_{i,t}}{\partial \tau} di \\
&\quad + \frac{\partial w_t}{\partial \tau}\left(1 - \int_0^1 l_{i,t} di\right) + \frac{\partial r_t}{\partial \tau}\left(a_t - \int_0^1 k_{i,t} di\right).
\end{aligned}$$

Applying market clearing conditions, we have:

$$\begin{aligned}
I_t &= \frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau} + \left[r_t - (1-\tau)\frac{\partial r_t}{\partial \tau}\right]\int_0^1 \Phi_i k_{i,t} di - \tau r_t \int_0^1 \frac{\partial k_{i,t}}{\partial \tau} di, \\
&= \frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau} + \left[r_t - (1-\tau)\frac{\partial r_t}{\partial \tau}\right]\int_0^1 \Phi_i k_{i,t} di - (1-\tau) r_t \int_0^1 \Phi_i \frac{\partial k_{i,t}}{\partial \tau} di + (1-\tau) r_t \int_0^1 \Phi_i \frac{\partial k_{i,t}}{\partial \tau} di - \tau r_t \int_0^1 \frac{\partial k_{i,t}}{\partial \tau} di, \\
&= \frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau} - \int_0^1 \frac{\partial}{\partial \tau}\left[(1-\tau) r_t \Phi_i k_{i,t}\right] di + \int_0^1 [(1-\tau)(1+\Phi_i) r_t - r_t]\frac{\partial k_{i,t}}{\partial \tau} di,
\end{aligned} \tag{31}$$

where the first term captures the general equilibrium effect of the subsidy, and the second term captures the change of extra capital expenditure due to existing MPK wedges.

Next, we will focus on the last term. First, denote the socially-optimal automation level as J_t^*, which can be pinned down by the following equation:

$$\gamma(J_t^*) = \frac{w_t}{r_t}.$$

Second, denote the aggregate capital demand in the decentralized economy as $K_t^{DE} = \int_0^1 k_{i,t} di$. Further, denote the optimal automation level of the dispersion-purged problem 2 as $\bar{J}_t$, which can be pinned down by the following equation:

$$\frac{\bar{J}_t}{1-\bar{J}_t}\gamma(\bar{J}_t) = K_t^{DE},$$

or in relative price expression:

$$\gamma(\bar{J}_t) = \frac{w_t}{(1+\bar{\Phi}_t)r_t},$$

where $\bar{\Phi}_t$ denotes the uniform borrowing cost that can generate the same aggregate capital demand K_t^{DE}. Note that all firms in the dispersion-purged problem 2 share the same optimal automation level $\bar{J}_t$. With K_t^{DE} and $\bar{J}_t$ in hand, we now decompose the last term of equation 31:

$$\begin{aligned}
\int_0^1 [(1-\tau)(1+\Phi_i)r_t - r_t]\frac{\partial k_{i,t}}{\partial \tau}di &= \int_0^1 [(1-\tau)(1+\Phi_i)r_t - w_t\gamma(\bar{J}_t)^{-1} + w_t\gamma(\bar{J}_t)^{-1} - r_t]\left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau} + \frac{\partial K_t^{DE}}{\partial \tau}\right]di, \\
&= \int_0^1 [(1-\tau)(1+\Phi_i)r_t - w_t\gamma(\bar{J}_t)^{-1}]\frac{\partial k_{i,t}}{\partial \tau}di + \int_0^1 [w_t\gamma(\bar{J}_t)^{-1} - r_t]\frac{\partial K_t^{DE}}{\partial \tau}di \\
&\quad + \int_0^1 [w_t\gamma(\bar{J}_t)^{-1} - r_t]\left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\right]di, \\
&= w_t\int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\frac{\partial k_{i,t}}{\partial \tau}di + w_t\left[\gamma(\bar{J}_t)^{-1} - \gamma(J_t^*)^{-1}\right]\frac{\partial K_t^{DE}}{\partial \tau} \\
&\quad + [w_t\gamma(\bar{J}_t)^{-1} - r_t]\int_0^1 \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\right]di.
\end{aligned}$$

Since $\int_0^1 k_{i,t}di = K_t^{DE}$, hence $\int_0^1 \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\right]di = 0$, which renders the last term zero.

In summary, the representative household's value function changes in the robot subsidy in the following way:

$$\frac{\partial V_t}{\partial \tau} = \sum_{s=0}^{\infty}\beta^s\lambda_{t+s}I_{t+s}, \tag{32}$$

where

$$\begin{aligned}
I_t = \underbrace{\frac{1}{\sigma}\frac{\partial Y_t}{\partial \tau}}_{\text{Wealth Effect}} &\underbrace{- \int_0^1 \frac{\partial}{\partial \tau}\left[(1-\tau)r_t\Phi_i k_{i,t}\right]di}_{\text{MPK Wedge Loss}} \\
&+ w_t\int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\frac{\partial k_{i,t}}{\partial \tau}di \quad + w_t\left[\gamma(\bar{J}_t)^{-1} - \gamma(J_t^*)^{-1}\right]\frac{\partial K_t^{DE}}{\partial \tau}.
\end{aligned} \tag{33}$$

Automation Dispersion Loss — Mean-Level Automation Gain

Next, we would like to show the signs of the *mean-level automation gain* and the *automation dispersion loss*.

Mean-Level Automation Gain: Trivially, $\frac{\partial K_t^{DE}}{\partial \tau} > 0$. Hence, whether this term is positive

or negative depends on $\gamma(\bar{J}_t)^{-1} - \gamma(J_t^*)^{-1}$. Hence, the *mean-level automation gain* becomes strictly positive if and only if $\bar{J}_t < J_t^*$.

Automation Dispersion Loss: To show that this term is always negative, we need to make the following decomposition:

$$
\begin{aligned}
w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \frac{\partial k_{i,t}}{\partial \tau} di &= w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}} + \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right] di, \\
&= w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(J_t^{cutoff})^{-1} + \gamma(J_t^{cutoff})^{-1}\gamma(\bar{J}_t)^{-1}\right] \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right] di \\
&\quad + w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}} di, \\
&= w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(J_t^{cutoff})^{-1}\right] \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right] di \\
&\quad + w_t \int_0^1 \left[\gamma(J_t^{cutoff})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right] di \\
&\quad + w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right] \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}} di,
\end{aligned}
\tag{34}
$$

where J_t^{cutoff} describes the cutoff value for $J_{i,t}$ such that $\frac{\partial}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}} > 0$ if and only if $J_{i,t} > J_t^{cutoff}$, which implies $\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}} > 0$ if and only if $J_{i,t} > J_t^{cutoff}$.[13] Hence, for the first term of Equation 34, $\gamma(J_{i,t})^{-1} - \gamma(J_t^{cutoff})^{-1}$ and $\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}$ always yield opposite signs:

$$
w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(J_t^{cutoff})^{-1}\right] \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right] di < 0.
$$

[13] More specifically, J_t^{cutoff} is the unique solution to a similar equation as Proposition 1: $\frac{\partial \log k}{\partial \tau} = \int_0^1 \frac{\partial \log k_{i,t}}{\partial \tau}\frac{k_{i,t}}{\int_0^1 k_{i,t} di} di$.

For the second term, since we have $\int_0^1 k_{i,t}di = K_t^{DE}$,

$$
\begin{aligned}
w_t \int_0^1 \left[\gamma(J_t^{cutoff})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right]di &= w_t\left[\gamma(J_t^{cutoff})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\int_0^1 \left[\frac{\partial k_{i,t}}{\partial \tau} - \frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}\right]di, \\
&= w_t\left[\gamma(J_t^{cutoff})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\left[\int_0^1 \frac{\partial k_{i,t}}{\partial \tau}di - \frac{\partial K_t^{DE}}{\partial \tau}\frac{1}{K_t^{DE}}\int_0^1 k_{i,t}di\right], \\
&= w_t\left[\gamma(J_t^{cutoff})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\left[\int_0^1 \frac{\partial k_{i,t}}{\partial \tau}di - \frac{\partial K_t^{DE}}{\partial \tau}\right], \\
&= 0.
\end{aligned}
$$

For the last term, applying $k_{i,t} = \frac{\sigma-1}{\sigma}\frac{1}{w_t}\gamma(J_{i,t})J_{i,t}p_{i,t}y_{i,t}$ we have:

$$
\begin{aligned}
w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}di &= w_t \int_0^1 \left[\gamma(J_{i,t})^{-1} - \gamma(\bar{J}_t)^{-1}\right]\frac{\partial K_t^{DE}}{\partial \tau}\frac{k_{i,t}}{K_t^{DE}}di, \\
&= \frac{\partial K_t^{DE}}{\partial \tau}\frac{1}{K_t^{DE}}\left[\int_0^1 w_t\gamma(J_{i,t})^{-1}k_{i,t}di - w_t\gamma(\bar{J}_t)^{-1}\int_0^1 k_{i,t}di\right], \\
&= \frac{\sigma-1}{\sigma}\frac{\partial K_t^{DE}}{\partial \tau}\frac{1}{K_t^{DE}}\left[\int_0^1 J_{i,t}p_{i,t}y_{i,t}di - \bar{J}_t Y_t^{Dispersion-Purged}\right], \\
&< 0.
\end{aligned}
$$

Note that $\int_0^1 J_{i,t}p_{i,t}y_{i,t}di$ and $\bar{J}_t Y_t^{Dispersion-Purged}$ represent the aggregate capital expenditure as a share of the total output in the decentralized economy and dispersion-purged economy, respectively. While removing the dispersion of MPK wedges improves the averaged automation level and the total output of the economy, the gap is constantly negative.

In summary, Equation 34, and hence the *automation dispersion loss* is constantly negative. ■

C.3 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), we 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 we neglect the time subscript:

Lemma 2 *Assume* $\gamma(x) = \exp(Ax)$ *and denote* $\Delta J_i = J_i - \bar{J}$. *The aggregate output* y *derived from the decentralized equilibrium can be expressed by:*

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

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

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

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

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

where $\mu_i = (1-\tau)(1+\Phi_i)r$ *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.

We 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 $\Delta J_i = 0$, we 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 we 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, we 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 3 *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 3 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 labor) 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 3, 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 3, 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, we conduct a numerical practice with parameter values $A = 2$, $\sigma = 5$ and $J = 0.33$. Figure C1 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 C2 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.

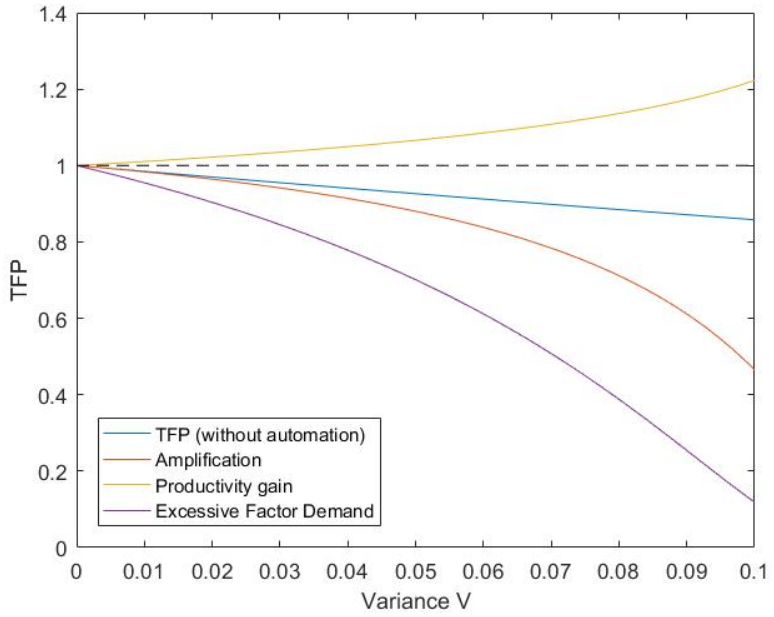


Figure C1: TFP Without Automation and Decomposition of TFP With Automation

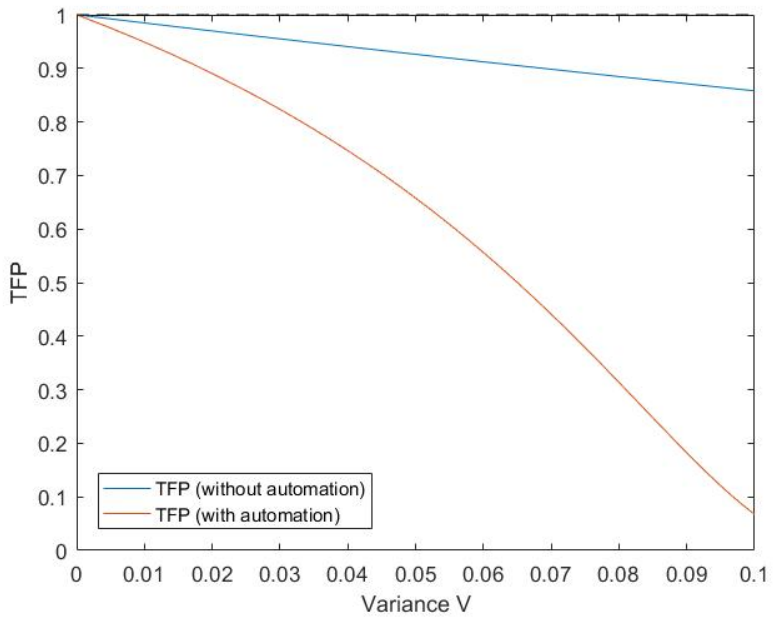


Figure C2: TFP Without Automation and TFP With Automation

D Calibration Details

We calibrate the full heterogeneous agent general equilibrium model incorporating endogenous borrowing costs and automation adoption to match the characteristics of China's industrial sector during 2010 - 2013.

D.1 Data Sources

Industrial Robot Stock and Density: We use industrial robot usage data from 2010 to 2013 obtained from the International Federation of Robotics (IFR), which provides annual installation and stock estimates for 45 industries across 100 countries and regions from 2001 to 2020.

Firm Characteristics: Firm-level statistics for 2010 are sourced from the Annual Survey of Industrial Enterprises (ASIE), which contains detailed annual financial data for approximately 300,000 above-designated-scale industrial firms in China.

Macro Aggregates: Additional macroeconomic parameters, such as the capital-to-output

ratio and labor share, are obtained from the National Statistical Yearbook.

D.2 Calibration Strategy

Overall Strategy

Our calibration rests on two key assumptions: (i) industrial robot adoption was negligible in 2010; and (ii) no automation-related subsidies existed before 2014. Based on these assumptions, we first calibrate the non-automation parameters, including traditional production technology, firm productivity distribution, and financial frictions—to match the characteristics of industrial firms in 2010. This ensures that these non-automation parameters capture the industrial characteristics free from the distortion of technology resulting from significant endogenous automation adoption.

Next, we calibrate the automation-related parameters to match the robot density and industrial robot stock growth between 2010 and 2013. Since there is no significant automation-related policy introduced during this period, the changes in robot adoption can be totally attributed to declining robot prices. As will be mentioned later, we assume that price of industrial robot declines at an annual rate of around 8%.

Externally Calibrated Parameters

We adopt standard values for the elasticity of substitution across varieties $\sigma = 7$ and the depreciation rate $\delta = 0.05$. The labor share of traditional technology is set at $\alpha = 0.6$, following labor share estimates from the 2010 National Statistical Yearbook. We adopt $\rho = 0.5$ for the elasticity of substitution across tasks, based on Humlum (2019), and $\nu = 0.85$ for the span of control parameter, as proposed by Restuccia and Rogerson (2008).

To calibrate the productivity distribution, we calculate firm-level TFP for 2010 using the approach in Hsieh and Klenow (2009), which yields a 75th-to-25th percentile ratio of approximately 3.5. We then set the mean and standard deviation of the log-productivity process to $\mu_z = -0.45$

and $\sigma_z = 0.95$, such that the mean of productivity is normalized to one while matching the empirical interquartile spread.

To estimate the elasticity of borrowing costs to asset position ω, we use firm-level data on fixed assets k_i, payroll wl_i, and total assets a_i for 2010 from ASIE. Assuming negligible robot adoption in 2010, the firm's first-order condition from the static problem (11) implies:

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

This yields the following nonlinear regression:

$$\log\left(\frac{k_i}{wl_i}\right) = \gamma_1 + \log\left(1 + \gamma_2 + \gamma_3 a_i^{\omega}\right) + \mu_s + \epsilon_i, \tag{35}$$

where ω captures the elasticity of borrowing cost with respect to assets. Estimation gives $\omega \approx -0.7996$. Since capital and payroll units are not directly comparable to those in the model, we do not calibrate β directly from γ_3, but instead choose it internally, the details of which will be described below.

D.2.1 Internally Calibrated Parameters

We calibrate the remaining parameters $\{\epsilon, p, c_f, \beta, z^m_{2010}, A\}$ as follows. The first five parameters are chosen to match moments in 2010; A is then chosen to match robot stock growth between 2010 and 2013.

We calibrate the preference parameters by setting the discount factor ϵ to match a capital-to-output ratio of 3, and selecting the dissipation rate p to yield a capital supply elasticity of 25, consistent with estimates from the literature (Moll et al., 2022). The fixed cost of firm entry, c_f, is chosen to target an average firm size of approximately 58.15 employees in 2010, sourced from the ASIE database.

As mentioned above, for financial frictions, we cannot directly use the parameter γ_3 estimated from the non-linear regression to calibrate the scale factor β. Instead, we calculate the implied capital utilization cost faced by the enterprise with averaged total asset using estimated coefficients and 2010 asset data as in Equation 35. This approach suggests an average borrowing premium of approximately 49.58%, which we target in the model by calibrating β to around 57.00.

Finally, to determine the two automation-related parameters, we first choose the productivity of the robotics sector in 2010, z^m_{2010}, by matching an observed robot density of about 30 industrial robots per 10,000 manufacturing employees, based on IFR robot stock data and ASIE employment data.

After pinning down the above parameters $\{\epsilon, p, c_f, \beta, z^m_{2010}\}$, we feed the model with an 8% annual increase in robotics productivity (corresponding to the observed decline in robot prices) and simulate the evolution of robot stock between 2010 and 2013. We then choose the automation comparative advantage parameter A to match the empirical annual growth rate of industrial robot stock of approximately 36%.