Robots Reshaping Spatial Dynamics: The Quantitative Effects of Robots on Chinese Firm' Relocation Trends

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Abstract: In a unified large-scale economy like China, the broad inland market is key on mitigating external shocks and promoting spatial growth. As firms' spatial distributions are important in developing the inland market and explaining market dynamics, we focus on how automation technologies, exemplified by robots, work as driving forces of firms' entry-exit dynamics and spatial distribution. We construct a multi-regional and multi-sectoral dynamic quantitative spatial equilibrium model that incorporates robots, firms' spatial distribution and labor migrations. We find that the inter-regional mobility of manufacturing firms exhibits a "spatial gradient" in China, which is driven by the intra-industry competition in eastern provinces, as well as the supply chains spillovers. We also show that subsidies for robots will increase local long-term equilibrium welfare and labor forces, where the increase effect on labor demand in inland areas from newly-located firms surpasses the decrease effect from the substitution of robots on labors. Our work implicates that subsidizing robots in inland areas will increase long-term welfare, while subsidies in coastal areas show little impact. Moreover, the inland area closest to coastal areas show most pronounced welfare benefits.

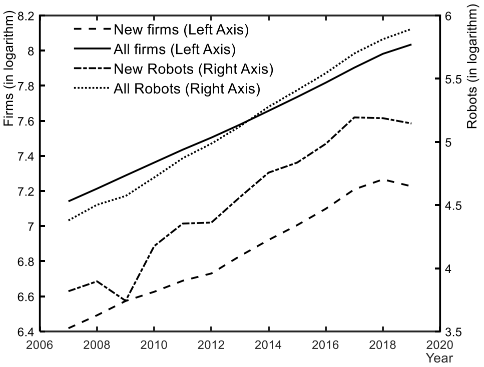
Key words: Robots; Firm Location; Dynamic Quantitative Spatial Equilibrium
JEL Classification: E20, O11

1 Introduction

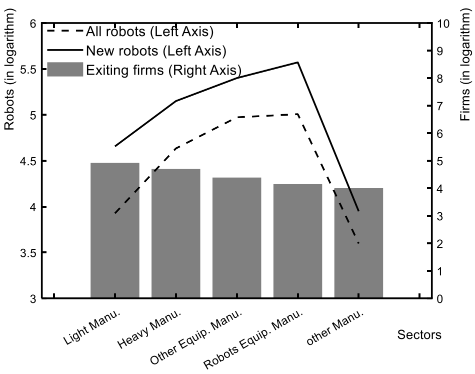
The spatial distribution of firms significantly influences the evolving geographic complexity of production networks, particularly in large-scale economies (Arkolakis et al., 2023). Consequently, understanding and quantifying the spatial dynamics of firms and employment have garnered substantial attention in academic research. Firm relocations driven by trade protectionism have become frequent subjects of debate (e.g., Caliendo and Parro, 2020), underscoring the importance of understanding the fundamental drivers behind firms' relocation decisions. In a unified economy, the extensive inland market plays a crucial role in buffering external shocks and fostering spatial economic growth, which can be inspired by the scale of production and firms. The entry and exit of firms are also essential for strengthening competitiveness in international trade (Arkolakis, 2016). Furthermore, coordinated regional development within a unified economy is closely driven by firm dynamics. Thus, we aim to investigate the direction, mode, and mechanisms of China's spatial distribution, focusing on firm entry and exit dynamics and spatial configurations.

Factor costs have been a more fundamental driver of firm dynamics beyond tariffs of trade policies as is explored in Suárez and Zidar (2016), Fajgelbaum et al. (2019) and Caliendo and Parro, (2020). Between 2012 and 2018, China's working-age population declined by over 26 million, leading to substantial increases in labor costs for firms. In response, the Chinese government has introduced policies promoting the production and utilization of robots to counter the trend of manufacturing outflows. The rise in labor costs has also promoted Chinese firms to use robots on a larger scale (Fan and Tang, 2021). In general, the widespread use of automation technologies such as robots will help to reduce the impact of rising labor costs on profits, attract firms to enter regions where traditional comparative advantages on labor have declined.

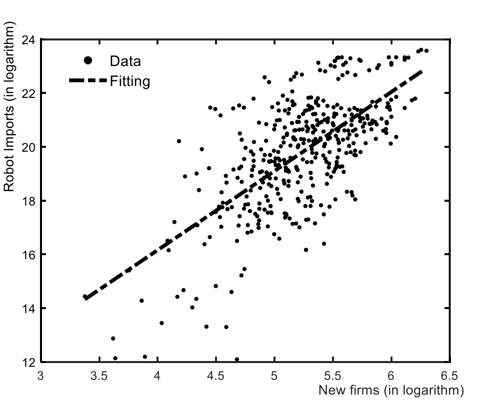
Macroeconomic data confirm these trends. As illustrated in Figure 1, from a national perspective, the parallel growth patterns between newly registered firms and robot adoption—as well as between total firm counts and robot inventory—support the economic intuition that an increase in robot usage may encourage firm establishment (Figure 1a). Examining firm retention across manufacturing sectors (Figure 1b), a negative correlation is observed between robot inventory and firm exits in most sectors. Notably, the robot-related equipment manufacturing sector shows the lowest firm exit rate and the highest levels of robot inventory and new additions, suggesting that robots may mitigate the adverse effects of rising labor costs and enhance firm stability within manufacturing sectors. At the regional level (Figure 1c), the total number of newly registered firms and robot imports across provinces is positively correlated. Furthermore, within each region (Figure 1d), a positive correlation exists between the number of surviving firms and robot imports, with eastern provinces having the highest numbers of surviving and newly registered firms, corresponding to its high levels of robot imports. These observations, spanning time, sector, and region, indicate that robot adoption may play a role in attracting firms and enhancing their rootedness within regions. This finding is particularly relevant to the modernization efforts of inland provinces from attracting firms from more developed coastal provinces.



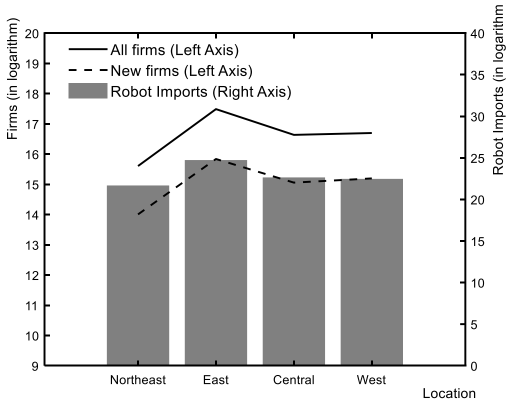
(a) National firms and robots by year;



(b) Manufactures and robots



(c) Provincial firms and robots' scatter plot;



(d) Firms and robot imports

Figure 1 Typical Facts of Firms and Robot Capital Investment in China

Data sources: Data on the annual and sectoral addition and use of robots in China, from the International Federation of Robotics (IFR); data on newly registered firms, existing firms, and exiting firms, from the National Firm Credit Information Publicity System; data on regional robot imports, from customs databases.

Building on these observations, we develop a framework to study the dynamics of labor and firms, specifically examining how robots are reshaping factor costs, and thus firms' spatial dynamics. Our model explicitly incorporates factor prices, firms' spatial decisions, labor migration, input-output linkages, and interregional trade to analyze the impact of factor-based policies. Our general equilibrium model incorporates a dynamic discrete choice framework for firms and labor, incorporating geographic features and input-output linkages. In our framework, firms operate within sectors across each province in China and foreign regions, producing intermediate goods that comprise each sector's market in a given region. These firms employ constant-returns-to-scale technology and source labor, robots, and materials from various markets. Within each monopolistically competitive sectoral market, firms make micro-level spatial decisions based on the trade-off between expected future profits and the residual value of market exit, à la (Suárez and Zidar, 2016). Factor costs—comprising labor and robot costs—directly influence firms' production costs and profitability. Firms' dynamic decisions collectively shape the macro-level size of each sector in each region, altering intermediate prices in equilibrium and amplifying the impact of robots on material costs. We define a "quasi scale effect" here as the impact of an increased number of firms in reducing intermediate prices.

On the labor supply side, households are forward-looking, supplying labor, receiving local competitive wages, and deciding whether to relocate or remain in their current location in the subsequent period, à la Caliendo and Parro (2019). We build our work on Caliendo and Parro (2019) , Caliendo and Parro (2020) and Bilal and Rossi-Hansberg (2021), which perform a "dynamic hat algebra" counterfactual analysis, by expressing the equilibrium conditions in relative time differences. We estimate trade elasticities, migration elasticities of firms and labors to obtain a more accurate value.

On the supply side of automated factors, robot manufacturers combine robots depreciated from the previous period with additional labor to supply robots for the subsequent period. Building on the frameworks of Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2022) and Restrepo et al. (2023), we decompose the creation of firm-specific value from basic input elements into several production "tasks." Firms can substitute between labor and automated factors (i.e., robots) for each "task, " with the allocation of each factor determined by factor prices and technological constraints. We calibrate the share of robotic tasks using the Inter-regional Input-Output Table and employ "dynamic hat algebra" to perform counterfactual analyses.

The number of operating firms determines the "quasi scale effect" in the general equilibrium. More firms will lower the intermediate prices faced by downstream firms in the equilibrium, as is the case in (Arkolakis et al., 2023), Carvalho et al. (2021) and Caliendo and Parro (2020). Besides the price effect, more firms in the same will dilute profits in the aggregate level of a region, while more firms in other sectors of the region will lower the intermediate costs and thus increase firms' profits through "quasi scale effect". Moreover, a trade-off exists between trade competition effect and supply chain spillover effect among the same sector in different regions. We incorporate all the above effects in our general equilibrium, and decompose these effects as the bunch of production network literatures do. Specifically, based on the theorem of production à la Carvalho et al. (2021) and Liu (2019), we decompose the *PEER COMPETITION EFFECT* in the same sector of the same region, the *SUPPLY CHAIN SPILLOVER EFFECT* in other sectors of the same region, the *TRADE-*

OFF SPILLOVER EFFECT in the same sector of other regions, and *SPILLOVER EFFECT* in other sectors of other regions in our quantifying framework.

In our general equilibrium model, the number of operating firms generates a "quasi scale effect," where an increase in firms reduces the intermediate prices faced by downstream firms, following the mechanisms observed in Arkolakis et al. (2023), Carvalho et al. (2021), and Caliendo and Parro (2020). Beyond this price effect, an increase in firms within the same sector of a region dilutes aggregate profits, while additional firms in other sectors reduce intermediate costs, thereby enhancing firm profitability through the "quasi scale effect". Additionally, a trade-off exists between the competition effects of trade and supply chain spillovers within the same sector across different regions. We integrate all these effects into our general equilibrium framework and decompose them similarly to approaches in the production network literature. Specifically, drawing on Carvalho et al. (2021) and Liu (2019), we quantify the following effects: the *Peer Competition Effect* within the same sector and region, the *Supply Chain Spillover Effect* across other sectors within the same region, the *Trade-off Spillover Effect* in the same sector across different regions, and the *Cross-Sector Spillover Effect* across other sectors in different regions. We demonstrate how our method can quantify the roles of supply chain spillovers, peer competition, trade competition, and other factors within a spatially quantified equilibrium. This production network-style decomposition supports our explanations of firm dynamics.

We apply our model to analyze firm dynamics using real data from 2017 across regions in China and foreign locations, examining the effects of China's robot subsidy policies on these dynamics. By applying our framework and solution methods, we explore the welfare and labor market impacts of robot subsidies à la Caliendo and Parro (2019). Our investigation focuses on the gap observed in labor demand: at the micro level, firms reduce labor needs due to substitution effect of automation (Fan and Tang, 2021), yet at the macro level, citywide employment rates show no significant decline (Dauth et al., 2021). A possible explanation for this discrepancy is that automation reshapes firms' spatial decisions and the scale of industries, leading to broad, marginal effects that influence employment patterns dynamically across regions. These structural changes may explain the observed stability in overall employment, as automation's impact appears offset by spatial and industrial shifts at the macroeconomic level.

Using our model, we quantify the extent to which robot subsidies impact firms' spatial distribution across various sectors, with a particular focus on manufacturing sectors. By computing the general equilibrium, we observe a nuanced difference between aggregate welfare changes across time and long-term welfare effects. Specifically, while robot subsidies may initially reduce welfare at the aggregate level, our model reveals positive labor market outcomes in the long-run stable equilibrium, where all variables reach convergence.

We apply a 2-country, 31-province, and 9-sector version of our model to assess the effects of robot subsidies on firm dynamics and labor distribution. Using data from 2017 on labor and firm distribution across markets, we calibrate the model to reflect that year's economic landscape. Our analysis incorporates all quantifiable regional-level automation policies from each Chinese province around 2017, capturing accurate proportions of subsidies allocated to automation technologies, specifically robots. These selected provinces are representative in terms of GDP and labor demand. To evaluate the impact of these subsidies, we design several counterfactual scenarios: the representative central province of Anhui, cancels its robot subsidies (Counterfactual 1 hereafter), three representative eastern provinces, Zhejiang, Tianjin, and Guangdong, cancel their robot subsidies (Counterfactual 2 hereafter). We also explore two scenarios where robot subsidies are increased, all central provinces increase their robot subsidies by 15 percentage (Policy Simulation 1 hereafter) and all western provinces increase their robot subsidies by 15 percentage (Policy Simulation 2 hereafter). Using our calibrated model and the counterfactual scenarios, the focus we aim to investigate is that, what would happen if robot subsidies were not implemented or were added?

As the manufacturing sector is a cornerstone of China's economy, our analysis primarily focuses on its response to changes in robot subsidies. We find that when the central province of Anhui withdraws its robot subsidies, the slowing trend in manufacturing firm exits is reduced. Specifically, by 2030, exit rates increase by 0.05% for both light and heavy industries, by 0.08% for robot manufacturing, and by 0.09% for other equipment manufacturing. When robot subsidies are canceled across the eastern provinces (Zhejiang, Tianjin, and Guangdong), the overall exit rate of manufacturing firms does rise slightly, though the effect is minor, indicating the region's resilience against subsidy changes. Our policy simulations reveal that increasing robot procurement subsidies by 15% in central provinces has a noticeable impact: by 2030, exit rates for light and heavy industries are projected to decline by 0.08%, affecting approximately 10,788 and 1,419 firms, respectively. Additionally, the robot manufacturing sector's exit rate would decrease by 0.1%, while other equipment manufacturing would see a slight increase of 0.1%. In western provinces, a 15% increase in subsidies is expected to decrease the exit rate by 0.08% for light industry, 0.07% for heavy industry, 0.1% for robot manufacturing, and 0.13% for other equipment manufacturing. In summary, our results suggest that increased subsidies significantly reduce exit rates across provinces, though the impact is less pronounced in the eastern provinces due to their economic resilience and mature manufacturing base. It is also shown that an extra subsidy on robots in central provinces will generate larger effect than in western provinces.

Our analysis of manufacturing firm entry rates in China reveals patterns consistent with firm exit rates, where the cancelation of subsidies will reduce the entry rate of each sector with eastern provinces show little impact. Moreover, an extra subsidy on robots in central provinces will generate larger effect than in western provinces.

To analyze changes in the stock of manufacturing firms, we examined each province's manufacturing share, revealing both trends similar to those seen in entry and exit rates and some distinct patterns. We identify a "gradient transfer" effect in the aggregate number of manufacturing firms, where central regions primarily attract firms from eastern provinces, and western regions attract firms from central provinces. Specifically, a 15% increase in robot subsidies in central provinces leads to a 0.27 percentage-point rise in their share of manufacturing firms (about 27,559 firms), with eastern provinces showing the most significant reduction (0.19 percentage points, or around 28,087 firms). Similarly, a 15% increase in subsidies in western provinces increases their share by 0.12 percentage points (approximately 14,404 firms), while the largest reduction occurs in central provinces (0.07 percentage points, or around 5,596 firms). This transfer pattern is influenced by two main dynamics: first, the manufacturing scale and competitive pressure in eastern regions drive firms toward central regions when nearby central provinces experience positive impacts, and towards eastern regions when negative impacts occur. Second, due to central provinces' smaller sectoral scale and limited supply chain support compared to eastern regions, western provinces tend to attract firms relocating from central areas, with the supply chain benefits outweighing competition pressures.

We examine the gap between macro- and micro-level impacts of robot subsidies on the labor market. Our findings reveal that, even without accounting for the "job creation effect" of automation technology, reducing subsidies for robot use actually decreases the local labor share. This outcome occurs because, at the macro level, the new employment opportunities generated by firms relocating to regional markets exceed the jobs displaced by robots substituting human labor at the micro level. Consequently, the relocation-driven demand for labor in these region counterbalances—and even outweighs—the substitution effect seen within individual firms.

We further investigate the welfare effects of robot subsidies as mentioned above. When Anhui cancels its robot subsidy, the welfare loss for the central region, where Anhui is located, is smaller than the long-run welfare loss. Initially, without the subsidy, the substitution of robots with labor increases labor demand, raising wages. However, as firms relocate away, labor demand and wages gradually decline, resulting in a long-term welfare loss of 1.0023%, which is larger than the initial welfare decline of 0.8151%. In contrast, other regions experience smaller long-term welfare losses, as firm entries stimulate labor demand and wage growth, ultimately reducing welfare losses over time. When robot subsidies are removed from eastern provinces, the effects are similar but much smaller in absolute terms. Conversely, when robot subsidies are raised by 15%, the regions implementing the subsidies initially experience welfare declines due to the "replacement of people with robots," with short-term welfare losses of 0.9031% in central provinces and 0.1287% in western provinces. However, these subsidies ultimately attract firms, resulting in substantial long-term welfare gains of 3.7149% in central provinces and 0.9077% in western provinces. Thus, while robot subsidies may have short-term welfare costs, they produce positive welfare gains in the long-term equilibrium by attracting firms. Additionally, our findings indicate that welfare gains from subsidies in central provinces tend to be higher in the long run compared to those in western provinces.

We believe that firm spatial layout will be affected by policy shocks: factor costs determine firm entry and exit decisions and spatial layout, which in turn determine the industrial scale of various regions and sectors. Industrial scale will affect the profits of local firms in this sector through local competition effects, and at the same time, affect the intermediate input costs and profits of firms engaged in production through the production cost supply chain spillover effects. This cycle continues to expand the impact. We quantify the cycle in our production network decomposition section as mentioned above, we find that the main push of firms' dynamics is from the *Peer Competition Effect* within the same sector and region, that is, more firms in the same sector and region will reduce product prices and dilute profits. It coinsides with our explanation of the "gradient transfer" from eastern provinces to central provinces. The main pull of firms' dynamics is from the local *Supply Chain Spillover Effect* across other sectors, that is, more firms in upstream and downstream sectors will reduce material costs and boost market scales. It also coinsides with our explanation of the "gradient transfer" from central provinces to western provinces. We also find that the factor costs themselves have little impacts, with almost all negative impacts from the *Peer Competition Effect* and positive impacts from the local *Supply Chain Spillover Effect.*

Our paper relates to recent studies of the effects of robots, automation technologies and artificial intelligence. Restrepo (2023); Aghion et al. (2017); Acemoglu and Restrepo (2018); Acemoglu and Restrepo (2022) have investigate different perspectives of robots. We verify that the employment effects at the firm level with our method are in line with the ones by Acemoglu and Restrepo (2018). Our contribution is toe provide a general equilibrium quantification of the level of employment effects of robots, as well as the aggregate and long-run welfare effects, discuss the important mechanisms, and perform policy simulations. We give another explannation of employment effects from firm dynamics, which helps explains the inconsistency between micro-level and macro-level.

Our approach also relates to a fast-growing strand of the literature that studies the impact on firm dynamics. We contribute to the DYNAMIC SPATIAL GENERAL EQUILIBRIUM as in Kleinman et al. (2023) and Caliendo and Parro (2019). We allow the firms to make their spatial decisions, and provide a more general framework. Our path dependence among periods is mainly from robot capitals, which can substitute labor with higher elasticities and different from Kleinman et al. (2023). We improve the micro-fundation of Suárez and Zidar (2016), who use productivities to explain firms' dynamics. Cost-driven channel to profits is proved in our work. We extend the equilibrium of Caliendo and Parro (2020) to investigate the driving mechanisms behind firms' spatial re-allocation and entry-exit decisions.

Our paper is also related to supply chain spillover as in Acemoglu and Tahbaz-Salehi (2020) and Baqaee (2018). They show that the exit of a firm can spread to other firms in the entire production network through its suppliers and customers, and can amplify the negative impact of supply chain disruptions through economies of scale. We examine the role of firm dynamics within a comprehensive general equilibrium framework, allowing us to uncover additional effects without heavily relying on analytical solutions. Besides, our quantifying consequences are not related to second-order approximations, and can capture more effect in higher-order effects. In this work, we define and quantify the role of the *Peer Competition Effect* within the same sector and region, the *Supply Chain Spillover Effect* across other sectors within the same region, the *Trade-off Spillover Effect* in the same sector across different regions, and the *Cross-Sector Spillover Effect* across other sectors in different regions.

Overall, we highlight three main departures of our paper from the previous literature. First, unlike recent dynamic discrete choice models focusing on firm reallocation, we incorporate a more flexible structure that allows firms to select their operating regions while considering comprehensive general equilibrium mechanisms such as trade flows, input-output linkages, and substitution between labor and robots. This framework provides a broad lens for analyzing factor adjustments beyond the confines of traditional trade barrier limitations. Second, we develop a method for decomposing the influence of each mechanism in our model, facilitating clearer interpretations in counterfactual scenarios. Lastly, our study complements theoretical research on automation by offering empirical insights into its differential effects on labor markets. Specifically, we investigate the apparent discrepancy where, despite automation substituting for labor at the firm level, employment rates remain relatively stable at the macro level. This approach allows us to assess welfare impacts more holistically by accounting for broader equilibrium effects.

The rest of this paper is arranged as follows: Section 2 outlines the framework of the dynamic quantitative spatial general equilibrium model. Section 3 describes the methods and data sources used for parameter calibration and estimation, followed by counterfactual analyses and policy simulations that explore the theoretical basis for changes in firm and labor distribution across China, as well as the welfare implications of relevant policies. Section 4 breaks down the factors influencing firm spatial distribution into competition effects, supply chain spillovers, and factor cost effects, providing an explanation by region and sector. Finally, Section 5 concludes the paper with a summary and offers policy implications based on the findings.

2 Theoretical Model

We construct a multi-region, multi-sector dynamic quantitative spatial general equilibrium model that includes the scale of robots. It assumes that the economy has N sectors, including an robot production sector, with each sector not only producing final goods but also intermediate goods. Superscripts j and k denote the corresponding sectors. The economy consists of M regions, denoted by superscripts i and n. Discrete time t is used.

2.1 Households

The theoretical construction of the household sector refers to Caliendo et al. (2019). It is assumed that in period $t = 0$, there is labor L_0^n in region n. The household sector provides one unit of labor each period and earns wages as income in a perfectly competitive labor market. After obtaining income each period, the household sector decides how to purchase final goods from different sectors to maximize utility. The consumption bundle in the utility function satisfies

$$C_t^n = \prod_{k=1}^{J} \left(C_t^{n,k}\right)^{\alpha^k} \tag{1}$$

where $C_t^{n,k}$ is the consumption of the final good of sector j by the household sector in region n in period t. It is assumed that the consumption share satisfies $\alpha^k \geq 0$， $\sum_{k=1}^{J} \alpha^k = 1$. The local ideal price index of period t and region n sector j's product price is denoted by P_t^{nk}, and the local ideal price index derived from equation (1) is

$$P_t^n = \prod_{k=1}^{J} \left(\frac{P_t^{nk}}{\alpha^k}\right)^{\alpha^k} \tag{2}$$

We assume that labor can freely flow between different sectors within the same region, but there is friction between different regions. Specifically, at the end of each consumption period, the household sector decides the location of labor for the next period based on expectations of future utility. If they move away from the current region n, they face relocation costs $Moving^{n,i} > 0$; if they do not move, they do not. In addition, the individual preferences of the household sector are denoted by ε_t^i, which follows a type I extreme value distribution with a mean of 0 and a dispersion parameter υ. The dynamic discrete choice model in Artuç et al. (2010) is used to characterize the labor migration decisions between different regions. The discount rate of the household sector is denoted by $\beta \geq 0$, and the total utility of the household sector in region n at time t is

$$u_t^n = log(C_t^n) + \max_{i=1,2,\cdots,N} \left\{\beta E_t\left(u_{t+1}^i\right) - Moving^{n,i} + \varepsilon_{t+1}^i\right\} \tag{3}$$

where $U_t^i = E_t\left(u_t^i\right)$ is the total expected utility of the household sector in region n. According to the properties of the type I extreme value distribution, the proportion of the household sector moving from region n to region i is $\mu_t^{n,i}$, with the proof provided in the Appendix.

$$\mu_t^{n,i} = \frac{exp\left(\frac{\beta U_{t+1}^i - Moving^{n,i}}{\upsilon}\right)}{\sum_{i'}^{N} exp\left(\frac{\beta U_{t+1}^{i'} - Moving^{n,i'}}{\upsilon}\right)} \tag{4}$$

where the expected utility satisfies

$$U_t^n = log(C_t^n) + \upsilon log\left(\sum\nolimits_{i'}^{N} exp\left(\frac{\beta U_{t+1}^{i'} - Moving^{n,i'}}{\upsilon}\right)\right) + \upsilon\bar{\gamma} \tag{5}$$

where $\bar{\gamma}$ is Euler's constant. According to equations (4) and (5), the dynamic layout of the household sector and labor between regions satisfies

$$L_{t+1}^{n} = \sum_{i=1}^{N} \mu_t^{i,n} L_t^{i} \tag{6}$$

2.2 Composite Intermediate Goods Production

Referring to Caliendo and Parro (2015) and Caliendo et al. (2018), we assume that there is an input-output relationship between firm sectors and considers the dynamic location choice and entry and exit decisions of firms in the intermediate goods market.

In a perfectly competitive composite intermediate goods market, for region n's sector j, firms produce the composite intermediate goods of their sector according to equation (7)

$$Q_t^{nj} = \left(\sum_{i=1}^{N} M_t^{ij} \left(q_t^{ij,nj}\right)^{\frac{\sigma^j - 1}{\sigma^j}} \right)^{\frac{\sigma^j}{\sigma^j - 1}} \tag{7}$$

where M_t^{ij} represents the number of firms in the local sector of region n; $\sigma^j > 1$ represents the substitution elasticity between firms from different regions within sector j; $q_t^{ij,nj}$ represents the intermediate goods purchased by firms in region n 's sector j from region i. According to equation (7), the intermediate goods demand function faced by firms in sector j of region n is

$$\frac{q_t^{ij,nj}}{Q_t^{nj}} = \left(\frac{p_t^{ij,n}}{P_t^{nj}} \right)^{-\sigma^j} \tag{8}$$

where $p_t^{ij,n}$ represents the price of intermediate goods purchased by firms in region n's sector j from region i, and $P_t^{nj} = \left(\sum_{i=1}^{N} M_t^{ij} \left(p_t^{ij,n}\right)^{1-\sigma^j} \right)^{\frac{1}{1-\sigma^j}}$ the ideal price index of intermediate goods. Thus, even if we do not introduce scale economies into the production function (an example can be seen in Zhong et al. (2023)), firms also have scale benefits: due to substitution elasticity $\sigma^j > 1$, the more upstream firms, the more they can reduce intermediate goods costs through competition within the same sector.

2.3 Intermediate Goods Production and the Role of Robots

We refer to Arkolakis et al. (2023) for setting the interdependence of intermediate goods production in sectors. It is assumed that the intermediate goods market is monopolistically competitive. Firms in the market determine their output based on market demand, trade costs, factor costs, and productivity for each period, where the labor input of sector j in region n is l_t^{nj}, the robots input is m_t^{nj}, and the intermediate goods purchased from sector k are $z_t^{k,nj}$. Firms in region n of sector j have a productivity a^{nj}, and the production function of the sector is

$$q_t^{nj} = a^{nj} \left(va_t^{nj}\right)^{\gamma^j} \prod_{k=1}^{J} \left(z_t^{k,nj}\right)^{\gamma^{k,j}} \tag{9}$$

where va_t^{nj} represents the basic input elements for the firm's own production, and the added value formed thereby accounts for the proportion γ^j of the firm's total output. We refer to the research of Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2022), Aghion et al. (2017), and Restrepo et al. (2023), and divides the process of forming the firm's own added value from the basic input elements into several production "tasks", that is

$$va_t^{nj} = \left(\int_0^1 \left(va_t^{nj}(z)\right)^{\frac{\zeta-1}{\zeta}} dz\right)^{\frac{\zeta}{\zeta-1}} \tag{10}$$

where $\zeta > 1$ is the substitution elasticity between different production tasks; $z \in [0,1]$ represents the production "task", where θ^j represents the lower limit of automatable tasks. The decrease in θ^j increases the range of production "tasks" that can be substituted by robots for labor, corresponding to the improvement of the automation level of the sector. Referring to Acemoglu and Restrepo (2022), the production "tasks" in the interval $[\theta^j, 1]$ can be produced by robots $m_t^{nj}(z)$ or labor $l_t^{nj}(z)$, and the two are perfectly substitutable; the production "tasks" in interval $[0, \theta^j]$ can only be produced by labor:

$$va_t^{nj}(z) = \begin{cases} A_L^{nj} l_t^{nj}(z) + m_t^{nj}(z) & if\ z \in [\theta^j, 1] \\ A_L^{nj} l_t^{nj}(z) & if\ z \in [0, \theta^j] \end{cases} \tag{11}$$

where A_L^{nj} represents the labor productivity of region n's sector j, that is, the production efficiency of using labor compared to robots in that sector.

The decision to use robots for production depends on factor costs. Let the price of robots be $P_t^{m,n}$ and there is an ad valorem subsidy $s^{m,n}$, the wage rate of labor is W_t^n, then in sector j of region n, the cost reduction caused by robots for a production "task" is $CS_t^{nj} = \frac{1}{1-\zeta}\left[1 - \left(\frac{A_L^{nj} P_t^{m,n}(1-s^{m,n})}{W_t^n}\right)^{1-\zeta}\right]$. When $CS_t^{nj} \geq 0$, $(1-s^{m,n})P_t^{m,n} < \frac{W_t^n}{A_L^{nj}}$, the cost of using robots is lower than the labor cost, and firms use automation technology for production; when $CS_t^{nj} < 0$, $(1-s^{m,n})P_t^{m,n} > \frac{W_t^n}{A_L^{nj}}$, the cost of using robots is higher than the labor cost, and firms still use traditional labor for production.

We define the threshold value of automatable tasks θ_A^{nj}:

$$\theta_A^{nj} = \begin{cases} (\theta^j)^\zeta & if\ CS_t^{nj} \geq 0 \\ 1 & if\ CS_t^{nj} < 0 \end{cases} \tag{12}$$

Then regions and sectors with higher labor productivity A_L^{nj} have a relatively larger threshold θ_A^{nj}. The added value production function of equation (10) can be rewritten as

$$va_t^{nj} = \left[(\theta_A^{nj})^{\frac{1}{\zeta}}(l_t^{nj})^{\frac{\zeta-1}{\zeta}} + (1-\theta_A^{nj})^{\frac{1}{\zeta}}(m_t^{nj})^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}} \tag{13}$$

from which the comprehensive cost of added value can be obtained as

$$p_t^{va,nj} = \left[\theta_A^{nj}\left(\frac{W_t^n}{A_L^{nj}}\right)^{1-\zeta} + (1-\theta_A^{nj})\left((1-s^{m,n})P_t^{m,n}\right)^{1-\zeta}\right]^{\frac{1}{1-\zeta}} \tag{14}$$

where $z_t^{k,nj}$ is the intermediate goods purchased by the firm from the local sector, and the proportion of the intermediate goods purchase amount to the total input of the firm is $\gamma^{k,j}$. According to the firm's cost minimization problem, the unit cost of firm inputs can be obtained

$$x_t^{nj} = B^{nj}\left(p_t^{va,nj}\right)^{\gamma^j} \prod_{k=1}^{J} \left(P_t^{nk}\right)^{\gamma^{k,j}} \tag{15}$$

where B^{nj} is the constant term composed of model parameters.

It is assumed that firms face iceberg costs $\tau^{ij,n} \geq 0$ in inter-regional transactions. Firms maximize profits sold to region i's sector j under the market demand constraint (8), and by the monopolistic competition market structure,

$$p_t^{ij,n} = \frac{\sigma^j}{\sigma^j - 1} \frac{\left(1 + \tau^{ij,n}\right) x_t^{ij}}{a^{ij}} \tag{16}$$

thus we obtain the total profit π_t^{nj} of the firm

$$\pi_t^{nj} = \sum_{i=1}^{N} \frac{1}{\sigma^j - 1} \frac{x_t^{nj}}{a^{nj}} \left(q_t^{nj,ij}\right) \tag{17}$$

2.4 Firm Dynamic Location Decision

We use a discrete choice model to characterize the location decision of firms. Similar model settings can be seen in Das et al. (2007) for the discussion of firm export decisions, and in Suárez and Zidar (2016) for the description of firm location based on regional productivity. Let v_t^{nj} be the value of the firm engaged in production in region n's sector j at time t (the discounted sum of future profits), and let v_t^{Oj} be the value of stopping production in sector j (the discounted sum of other potential locations). The income of firms in each period may be affected by idiosyncratic shocks (denoted by ϵ_t^{nj} and ϵ_t^{Oj} respectively), so before the shock, firms can only form expectations of future value. Let the expected value of future production for a representative firm be $V_{t+1}^{nj} \equiv E_t\left(v_t^{nj}\right)$; the expected value of stopping production for an firm be $V_{t+1}^{Oj} \equiv E_t\left(v_t^{Oj}\right)$. It is assumed that the discount rate faced by entrepreneurs when earning profits is the same as that of the household sector.

In period t, firms engaged in production in region n's sector j earn profits π_t^{nj} and decide whether to stay in the local area to continue production in the next period, thus

$$v_t^{nj} = \pi_t^{nj} + \max_{n,O}\left\{\beta V_{t+1}^{nj} + \epsilon_t^{nj}; \beta V_{t+1}^{Oj} + \epsilon_t^{Oj}\right\} \tag{18}$$

Stopping production firms do not earn any profits, but after stopping production in the next period, they can choose a new production location. Firms entering a new region to engage in production need to invest to obtain the fixed cost ϖ_t^n of production in region n at time t

$$v_t^{Oj} = \max_{h \in \{1,2,\cdots,N,O\}}\left\{\beta\left(V_{t+1}^{hj} - \varpi_{t+1}^{h}\right) + \epsilon_t^{hj}\right\} \tag{19}$$

It is assumed that idiosyncratic shocks are independently and identically distributed according to the type I extreme value distribution, with a mean of 0 and a dispersion parameter . $\mathcal{V}$ Then, according to the properties of the type I extreme value distribution, the expected values of firms engaged in production and stopping production can be obtained. The proof is in our Appendix.

$$V_t^{nj} = \pi_t^{nj} + \mathcal{V}\bar{\gamma} + \mathcal{V} \log\left[\sum_{h=O,n} \exp\left(\frac{\beta V_{t+1}^{hj}}{\mathcal{V}}\right)\right] \tag{20}$$

$$V_t^{Oj} = \mathcal{V}\bar{\gamma} + \mathcal{V} \log\left[\sum_{h \in \{1,2,\cdots,N,O\}} \exp\left(\frac{\beta\left(V_{t+1}^{hj} - \varpi_{t+1}^{h}\right)}{\mathcal{V}}\right)\right] \tag{21}$$

where equation (21) indicates that exiting production does not mean that the future value is zero. Stopped production firms may have a positive value, which is because when firms exit production from a certain area, it also means that firms can choose to engage in production in other regions to obtain higher value. Let $\varphi_t^{nj,nj}$ be the proportion of firms in nj that continue to engage in production locally, according to the properties of the type I extreme value distribution

$$\varphi_t^{nj,nj} = \frac{\exp\left(\frac{\beta}{\mathcal{V}} V_{t+1}^{nj}\right)}{\sum_{h=O,n} \exp\left(\frac{\beta}{\mathcal{V}} V_{t+1}^{hj}\right)} \tag{22}$$

The proportion of firms stopping production is $\varphi_t^{nj,Oj} = 1 - \varphi_t^{nj,nj}$. Similarly, let $\varphi_t^{Oj,nj}$ be the proportion of firms that stopped production in the previous period and choose to enter the market nj to engage in production in the next period, if they still do not engage in production in the next period, then $n = O$:

$$\varphi_t^{Oj,nj} = \frac{\exp\left(\frac{\beta}{\mathcal{V}}\left(V_{t+1}^{nj} - \varpi_{t+1}^{n}\right)\right)}{\sum_{h\in\{1,2,\cdots,N,O\}} \exp\left(\frac{\beta}{\mathcal{V}}\left(V_{t+1}^{hj} - \varpi_{t+1}^{h}\right)\right)} \tag{23}$$

Finally, we organize the transition equations for the two types of firms. Let the number of firms engaged in production be M_t^{nj}, and the number of firms that have stopped production be M_t^{Oj}, then

$$M_{t+1}^{nj} = M_t^{nj}\varphi_t^{nj,nj} + M_t^{Oj}\varphi_t^{Oj,nj} \quad \forall n,j \tag{24}$$

$$M_{t+1}^{Oj} = \sum_{h\in\{1,2,\cdots,N,O\}} M_t^{hj}\varphi_t^{hj,Oj} \quad \forall j \tag{25}$$

2.5 Supply of Robots

We regard robots as a product of the robot-related equipment manufacturing industry, using superscript au to represent manufacturers specializing in the production of robots. We assume that these manufacturers pay a land price ϖ_t^n to local residents when entering, and there are a large number of potential manufacturers, so it is zero profit. These manufacturers provide robots for various intermediate goods firms at the end of each period, using the robots and labor of the previous period to produce new robots for the next period, and the old robots depreciates at a rate δ per period. Therefore, the production function of specialized robot manufacturers is

$$m_t^n = [(1-\delta)m_{t-1}^n]^{\kappa}(l_t^{n,au})^{1-\kappa} \tag{26}$$

where m_{t-1}^n represents the robot stock of manufacturer in period $t-1$, and m_t^n represents the newly produced robots; κ represents the labor income share in the robot production process, $l_t^{n,au}$ represents the labor input of the representative robot manufacturer in region n, and earns wages W_t^n in each period. In equation (26), since we assume that robots can flow between different sectors within the same region, and all sectors have the same robot reproduction function, the superscript j representing the sector is omitted. According to the first-order condition, and summing up all robot manufacturing firms, we get

$$W_t^n L_t^{n,au} = (1-\kappa)P_t^{m,n} Me_t^n \tag{27}$$

where $L_t^{n,au}$ is the total labor input of robot manufacturers in region n. The total robot stock in the region n after aggregation is

$$Me_t^n = [(1-\delta)Me_{t-1}^n]^{\kappa}(L_t^{n,au})^{1-\kappa} \tag{28}$$

2.6 Equilibrium

The proportion of intermediate goods from region n used by the sector j in region i when producing final goods is denoted by $\lambda_t^{nj,i}$, and it can be seen from equations (8) and (16) that

$$\lambda_t^{nj,i} = \frac{M_t^{nj}\left[\left(1+\tau^{nj,i}\right)x_t^{nj}\right]^{1-\sigma^j}\left(a^{nj}\right)^{\sigma^j-1}}{\sum_{h=1}^{N} M_t^{hj}\left[\left(1+\tau^{hj,i}\right)x_t^{hj}\right]^{1-\sigma^j}\left(a^{hj}\right)^{\sigma^j-1}} \tag{29}$$

The total income of the region is characterized by I_t^n. We also denote $\chi_t = \sum_{i=1}^{N}\sum_{k=1}^{J} M_t^{ik}\pi_t^{ik}$ the total profits, assuming that each region's firms are allocated a fixed proportion ι^n of the total profits, thus consuming local products. Besides, all subsidies should be removed from total incomes. Therefore,

$$I_t^n = W_t^n\left(L_t^{n,au} + \sum_{j=1}^{J} L_t^{nj}\right) + \varpi_t^n + \iota^n\chi_t - s^{m,n}P_t^{m,n}Me_t^n \tag{30}$$

According to the zero-profit condition of robot equipment manufacturers, equation (30) can be rewritten as

$$I_t^n = W_t^n\left(\sum_{j=1}^{J} L_t^{nj}\right) + \left(1-s^{m,n}\right)P_t^{m,n}Me_t^n + \iota^n\chi_t \tag{31}$$

X_t^{nj} represents the total expenditure of the region n's sector j (including the purchase of intermediate goods and final goods)

$$X_t^{nj} = \sum_{k=1}^{J}\gamma^{j,k}\sum_{i=1}^{N}\left(1-\frac{1}{\sigma^k}\right)\lambda_t^{nk,i}X_t^{ik} + \alpha^j I_t^n \tag{32}$$

The labor market clearing condition for non-automation capital manufacturing firms is

$$W_t^n L_t^n = W_t^n\sum_{j=1}^{J} L_t^{nj} = \sum_{j=1}^{J}\theta_A^{nj}\left(\frac{W_t^n}{A_L^{nj}p_t^{va,nj}}\right)^{1-\zeta}\gamma^j\sum_{i=1}^{N}\left(1-\frac{1}{\sigma^j}\right)\lambda_t^{nj,i}X_t^{ij} \tag{33}$$

The market clearing condition for robots is

$$\left(1-s^{m,n}\right)P_t^{m,n}Me_t^n = \sum_{j=1}^{J}\left(1-\theta_A^{nj}\right)\left(\frac{\left(1-s^{m,n}\right)P_t^{m,n}}{p_t^{va,nj}}\right)^{1-\zeta}\gamma^j\sum_{i=1}^{N}\left(1-\frac{1}{\sigma^j}\right)\lambda_t^{nj,i}X_t^{ij} \tag{34}$$

3 Analysis of the Impact of robots

3.1 Data and Estimation

We refer to the dynamic "dynamic exact hat algebra" defined by Caliendo et al. (2019) and Caliendo and Parro (2020), capturing the additional changes caused by shocks relative to the benchmark situation, thus excluding the changes in the economy itself without shocks. The model equilibrium can be defined as follows.

Given the initial state of the economy $\left\{L_0^n, U_0^n, \mu_0^{n,i}, M_0^{nj}, \varphi_0^{Oj,nj}, \varphi_0^{nj,nj}, V_0^{nj}, Me_0^n, \varpi_0^n, P_0^{m,n}, W_0^n\right\}_{n=1;j=1}^{N+1;J}$, as well as existing policies, iceberg costs, and profit distribution ratios $\left\{s^{m,n}, \tau^{nj,i}, \iota^n\right\}_{n=1}^{N+1}$, the endogenous variables

$$\left\{\left\{\begin{matrix} L_t^n, U_t^n, \mu_t^{n,i}, M_t^{nj}, \varphi_t^{Oj,nj}, \varphi_t^{nj,nj}, V_t^{nj}, Me_t^n, P_t^{m,n}, W_t^n, C_t^n, P_t^n, p_t^{ij,n}, P_t^{nj}, \\ p_t^{va,nj}, x_t^{nj}, \pi_t^{nj}, \lambda_t^{nj,i}, \chi_t, I_t^n, X_t^{nj} \end{matrix}\right\}_{i,n=1;j=1}^{N+1;J}\right\}_{t=0}^{\infty}$$

satisfying the equilibrium conditions are determined.

The period in our model corresponds to one year of data, and the real data and processing process are briefly described as follows.

I. Labor Data

To determine the labor quantity of each region at the base period, we use the proportion of the population aged 15-65 from the 2020 Seventh National Population Census, combined with the year-end population numbers of each province in the “China Statistical Yearbook” to determine the total labor quantity of each region. Labor data from other countries come from the Penn World Table. To determine the base period labor migration rate, we use the migration data between regions in the Baidu Migration Database, summarized by region to form the base period population migration matrix. The base period wage level is calibrated based on the “China Statistical Yearbook”.

II. Trade Data

For domestic trade, we use the multi-region input-output table compiled by Chen et al. (2023), using data from 31 provinces at the base period. For trade data between domestic and foreign regions, we use the OECD input-output table, unifying foreign regions as RoW (rest of the world), and merging the multi-region input-output table and the OECD input-output table. The merged table includes 31 regions in the country and 1 merged world other region (RoW). We divide the table into 9 sectors, namely agriculture, forestry, animal husbandry, and mining, light industry, heavy industry, robot equipment manufacturing, other equipment manufacturing, other manufacturing, construction, wholesale and retail trade, and service industry. The specific sector division standards are referred to in Appendix 1.

III. Firm Entry, Exit, and Spatial Layout Data

Using the comprehensive information data of industrial and commercial registration in China, we organize the registration and cancellation of firms in each year, in each sector (industry), and in each region, and calculates the number of existing firms in each province that year based on the number of firms surviving in the previous year, the number of cancellations, and the number of registrations that year. The number of firms abroad is assumed to be proportional to the domestic firms, with the ratio of firm quantities in domestic and foreign sectors roughly the same as the relative GDP of domestic and foreign sectors. Domestic and foreign sectoral relative GDP information comes from the OECD database, and the entry and exit probabilities of foreign sectors come from the firm statistics database (Birth rate of Firms and Death rate of Firms) in the OECD database.

To calibrate the base period firm exit rate, we use the number of firms cancelled in the base period / the number of firms surviving in the base period from the above database; to calibrate the base period firm entry rate, we use the total number of firms entering each sector in the base period / the total number of firms entering each sector in the country in the base period.

IV. Entry Cost

To obtain the entry cost of firms in the base period, we use the national land transaction data in 2017, summarized to the province, and calculates the average industrial land price based on the transaction price and area data of industrial land transactions in each province. The data comes from the China Land Market Network.

V. Robot-related Data

To obtain the robot stock in each region at the base period, we refer to the employment personnel’s split approach of Wang and Dong (2020), which decomposes the industry-level industrial robot installation situation to the regional level. Specifically, we first use the industrial robot installation quantities of various industries in China published by the International Federation of Robotics (IFR), and collects the employment personnel of each province in the “China Labor Statistics Yearbook” to account for the national total employment personnel. The percentage is used to multiply the national industry robot installation quantity, and then the industry is summed up to obtain the total robot stock in each region of the country at the base period.

To calibrate the base period robot price, we use the customs industrial robot import data from 2015 to 2017 to calculate the average price of industrial robots in the base period. The HS 8-digit code range used for calculating the import price of robots is shown in Table 1. Due to the lack of import data in Tibet and Qinghai, a broader statistical dimension is used in the table, marked in parentheses.

Table 1 The data used to calculate the robots' prices in 2017

HS8 code	HS8 code
84248920	84798910 (For Tibet and Qinghai)
84289040	84798920 (For Tibet and Qinghai)
84795010	84798940 (For Tibet and Qinghai)
84795090	84798950 (For Tibet and Qinghai)
84864031	84798961 (For Tibet and Qinghai)
85152120	84798962 (For Tibet and Qinghai)
85153120	84798969 (For Tibet and Qinghai)
85158010	84798992 (For Tibet and Qinghai)
84798999 (For Tibet and Qinghai)	85152191 (For Tibet and Qinghai)
85152199 (For Tibet and Qinghai)	

VI. Parameter Calibration and Estimation

The subjective discount factor β is commonly set to 0.99. The final consumption share of each sector $\{\alpha^k\}_{k=1}^{J}$ is calibrated as the proportion of residents' final expenditure on different industries in the input-output table. The distribution parameter = of individual preferences υ in the household sector, referring to the coefficient estimation results of Chen and Zhao (2023), is set to 5.7985. The elasticity $\sigma^j = 4$ is taken from Tombe and Zhu (2019) and Chen and Zhao. The added value coefficient γ^j is calibrated as the ratio of added value to total input in the input-output table. The labor input in the added value production of each sector is calibrated based on the ratio of labor remuneration to added value in the input-output table. The substitution elasticity ζ between robots and labor in the production of added value in the intermediate goods production sector is set to 1.28[1]. The upstream intermediate goods input of the intermediate goods production sector $\gamma^{k,j}$ is calibrated as the ratio of the input value of each upstream intermediate goods in each sector to the total input value in the input-output table. The labor remuneration share in the robot production sector $1-\kappa$ is regarded as the ratio of labor remuneration to total output in the robot-related equipment manufacturing industry, which is 0.48.

To calibrate the iceberg cost between regions, we refer to Tombe and Zhu (2018) and measures the trade barriers through the proportion of inter-regional trade.

$$\frac{\lambda_t^{nj,n}\lambda_t^{ij,i}}{\lambda_t^{nj,i}\lambda_t^{ij,n}} = \left[\left(1+\tau^{nj,i}\right)\left(1+\tau^{ij,n}\right)\right]^{\sigma^j-1}$$

To calibrate the share of each region in the global profit mix ι^n, we refer to Caliendo et al. (2019) and Caliendo and Parro (2020) and calibrates it based on the data of the input-output table in the base period. Specifically, let

$$\iota^n = \frac{\sum_{j=1}^{J}\frac{1}{\sigma^j}\sum_{i=1}^{N}\lambda_t^{nj,i}X_t^{ij}}{\chi_t}$$

For the distribution parameter $\mathcal{V}$ of Chinese firms, there is currently no direct support from existing data. We construct the following regression equation to estimate $\mathcal{V}$, referring to Caliendo and Parro (2020):

$$\log\frac{\varphi_{t-1}^{nj,nj}}{\varphi_{t-1}^{nj,0j}} + \beta\log\frac{\varphi_t^{nj,nj}}{\varphi_t^{0j,nj}} = \frac{\beta}{\mathcal{V}}\pi_t^{nj} + d_t^n + \tilde{C}_t + \varepsilon_t^{nj}$$

where $\tilde{C}_t$ is the time trend term, d_t^n is the time-region-level fixed effect, and ε_t^{nj} is the residual term. The error may come from the estimation bias of $\varphi_t^{0j,nj}$, which captures the potential firms that have not entered the market in the global total but does not include the potential entrants that have not been observed. We assume that the estimation bias is orthogonal to profits, referring to Caliendo and Parro (2020). To further overcome the endogeneity problem, we introduce the Bartik profit instrument variable, referring to Chen and Zhao. All estimation results are shown in our Appendices. The estimated coefficient $\beta/\mathcal{V}$ is always significantly positive, and the value is relatively stable in different regressions, with an average value of 0.0422, so the final is obtained $\mathcal{V} = 23.4518$.

VII. Policy Simulation

To simulate the impact of regional robot use on the entry and exit dynamics and spatial layout of firms, we collect the incentive policies related to robot procurement subsidies in various regions from 2017 to 2018, thus calibrating the model parameter $s^{m,n}$. These policies are mostly concentrated in eastern provinces, as shown in our Appendices. Due to the quantifiability of policies, we select Anhui (8%) as the representative incentive policy in central provinces, and the simulation scenario where this policy is canceled is recorded as counterfactual scenario 1; Tianjin (15%), Zhejiang (10%), and Guangdong (10%) are selected as the representative incentive policies in eastern provinces, and the simulation scenario where these policies are canceled is recorded as

[1] For this elasticity of substitution, Galle and Lorentzen (2024) takes value 1.28, and Berg et al. (2018) takes 2.5 as the minimum elasticity of substitution. We take 2 in the counterfactual simulation and policy analysis, and substitutes the methods of Galle and Lorentzen (2024) and Berg et al. (2018) to find that the prediction error of the proportion of firms in each region in the manufacturing industry is within 0.0123%.

counterfactual scenario 2. In addition, we simulate the situation where all central regions increase the robot procurement subsidy by 15%, recorded as policy simulation scenario 1; the situation where all western regions increase the robot procurement subsidy by 15%, recorded as policy simulation scenario 2.

3.2 Model's Explanation of Reality

The fitting situation of the model in the first five years is shown in Table 2. From the trend, both the equilibrium results and the real data show a trend of the proportion of manufacturing firms in the eastern and northeastern regions decreasing year by year, and the proportion of manufacturing firms in the central and western regions increasing year by year, which is relatively consistent. In terms of numerical results, the maximum error is within 1.1654% (absolute difference), not exceeding 7.7139% of the base value (relative difference), so the model's explanation of reality is relatively good. As mentioned above, we use $\zeta = 1.28$. To test the impact of its value on the equilibrium results, we have conducted robustness tests on the equilibrium results of $\zeta = 2$ and $\zeta = 2.5$, and the results are shown in our appendices. It can be seen that the simulation results about the substitution elasticity of labor ζ and robots are robust.

Table 2 Manufacturing firms' regional share

Year	Eastern provinces		Northeastern provinces		Central provinces		Western provinces	
	Model	Data	Model	Data	Model	Data	Model	Data
2017	64.3900%	64.3900%	6.1805%	6.1805%	15.6687%	15.6687%	13.7608%	13.7608%
2018	63.7939%	63.2565%	6.1274%	6.0877%	16.1345%	16.4815%	13.9441%	14.1743%
2019	63.2898%	62.5132%	6.0795%	5.8952%	16.5611%	17.0707%	14.0695%	14.5209%
2020	62.8805%	61.8058%	6.0336%	5.6673%	16.9455%	17.6059%	14.1405%	14.9211%
2021	62.5405%	61.3751%	5.9890%	5.5601%	17.2964%	17.9450%	14.1741%	15.1198%

3.3 Exiting Rate of Firms

The firm exit rates in the manufacturing sector of various counterfactual regions under four scenarios are shown in Figure 2. Figure 2 shows that under counterfactual scenario 1, where Anhui cancels the robot subsidy (Figure 2(a)), the trend of the manufacturing firm exit rate slowing down is mitigated. By 2030, the exit rate of light industry will increase by 0.05%, heavy industry by 0.05%, robot manufacturing by 0.08%, and other equipment manufacturing by 0.09%. Under counterfactual scenario 2, where eastern provinces cancels the robot subsidy (Figure 2(b)), the overall manufacturing firm exit rate shows an increasing trend, but the impact on the exit rate is small. In addition, the exit rate of light and heavy industries in central provinces shows a trend of first increasing and then decreasing, while the robot and other equipment manufacturing industries show a decreasing trend, and the overall manufacturing exit rate in western provinces shows a trend of first increasing and then decreasing.

In terms of policy simulation, under policy simulation scenario 1, where central provinces increases the robot procurement subsidy by 15% (Figure 2(c)), the light industry exit rate in 2030 will decrease by 0.08% (involving 10,788 firms), the heavy industry exit rate will decrease by 0.08% (involving 1,419 firms), the robot manufacturing industry will decrease by 0.1%, and other equipment manufacturing will increase by 0.1%. Under policy simulation scenario 2, where western provinces increases the robot procurement subsidy by 15% (Figure 2(c)), the light industry exit rate in 2030 will decrease by 0.08%, the heavy industry exit rate will decrease by 0.07%, the robot manufacturing industry will decrease by 0.10%, and other equipment manufacturing will decrease by 0.13%.

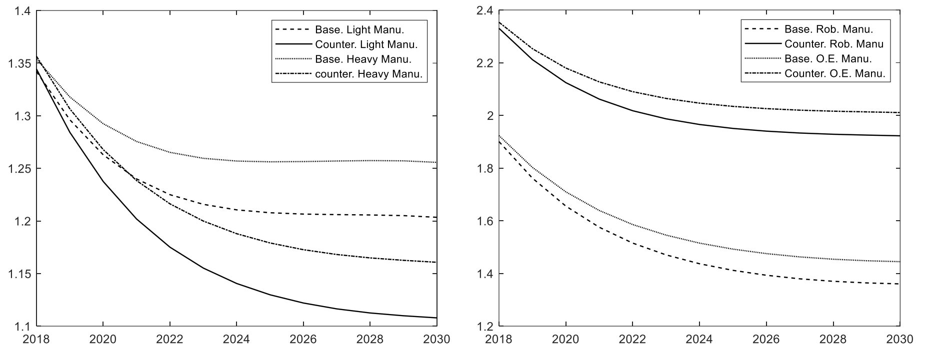


Figure 2 (a) Counterfactual 1

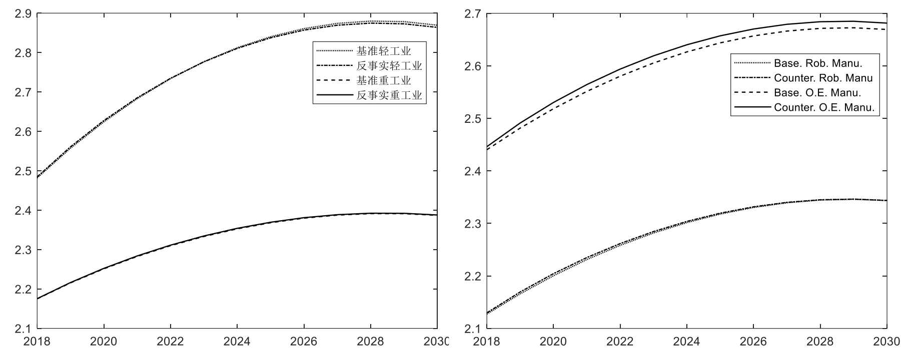


Figure 2 (b) Counterfactual 2

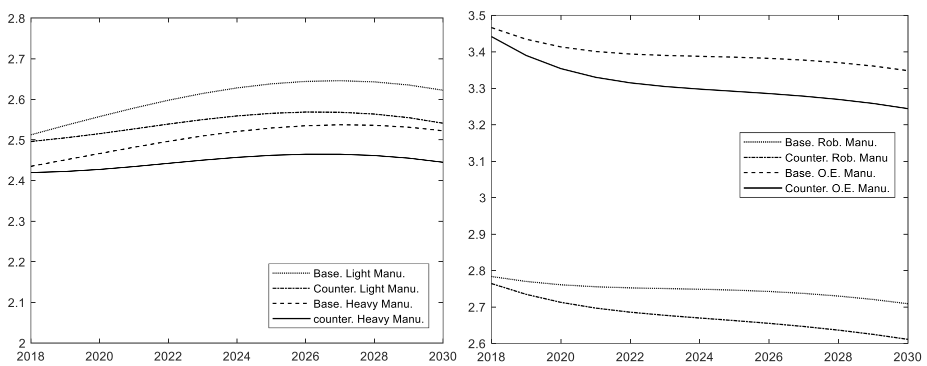


Figure 2 (c) Policy Simulation 1

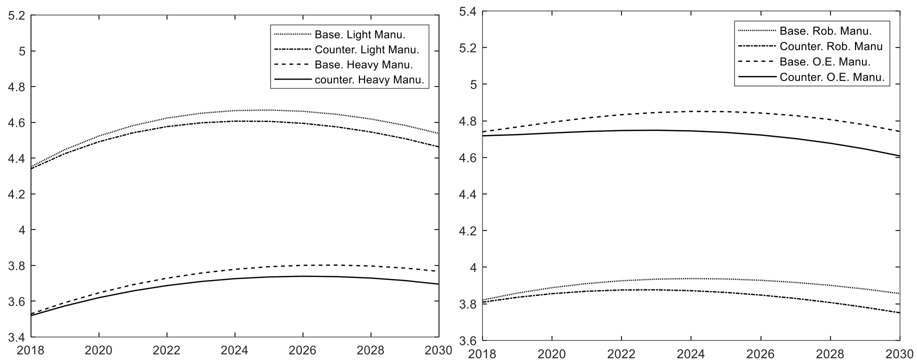


Figure 2 (d) Policy Simulation 2

Figure 2 Firms' exit rate in various scenarios

3.4 Entry Rate of Firms

The firm entry rates in the manufacturing sector of various counterfactual regions under four scenarios are shown in Figure 3. Figure 3 shows that the entry rate of light industry firms in Anhui shows a trend of first increasing and then decreasing, while the entry rates of heavy industry, robot, and other equipment manufacturing industries show an increasing trend; the entry rates of light and heavy industry firms in eastern provinces overall show a decreasing trend, while the robot and other equipment manufacturing industries overall show an increasing trend; the overall entry rate of manufacturing firms in central provinces shows a decreasing trend; the overall entry rate of manufacturing firms in western provinces shows a decreasing trend.

Under counterfactual scenario 1, where Anhui cancels the robot procurement subsidy (Figure 3(a)), by 2030, the entry rate of light industry will decrease by 0.09%, heavy industry by 0.1%, robot manufacturing by 0.09%, and other equipment manufacturing by 0.04%. Under counterfactual scenario 2 (Figure 3(b)), the cancellation of the robot procurement subsidy in eastern provinces has a small impact on the entry rate of manufacturing firms in eastern provinces. Under policy simulation scenario 1 (Figure 3(c)), where central provinces increase the robot procurement subsidy by 15%, by 2030, the entry rate of light industry will increase by 0.33%, heavy industry by 0.39%, robot manufacturing by 0.27%, and other equipment manufacturing by 0.13%. Under policy simulation scenario 2 (Figure 3(d)), if western provinces increase the robot procurement subsidy by 15%, the trend of the manufacturing firm entry rate decreasing will slow down, and by 2030, the entry rate of light industry will increase by 0.18%, heavy industry by 0.19%; robot manufacturing will increase by 0.16%, and other equipment manufacturing by 0.05%.

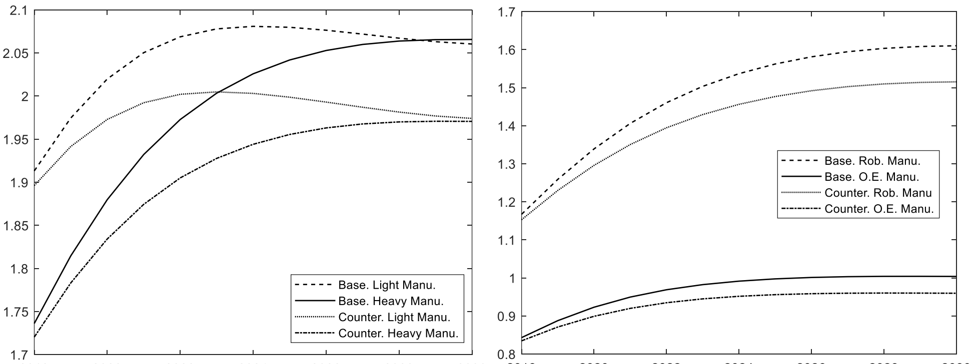


Figure3(a) Counterfactual 1: Firm migration rate in Anhui

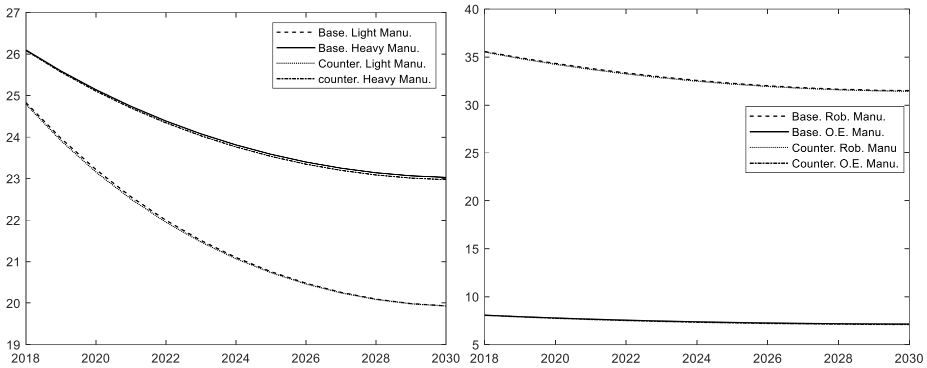


Figure3(b) Counterfactual 2: Firm migration rate in East

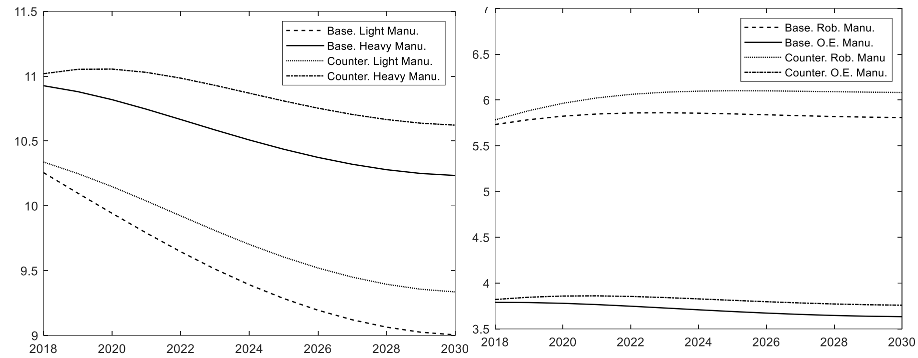


Figure3(c) Policy simulation 1: Firm migration rate in Central

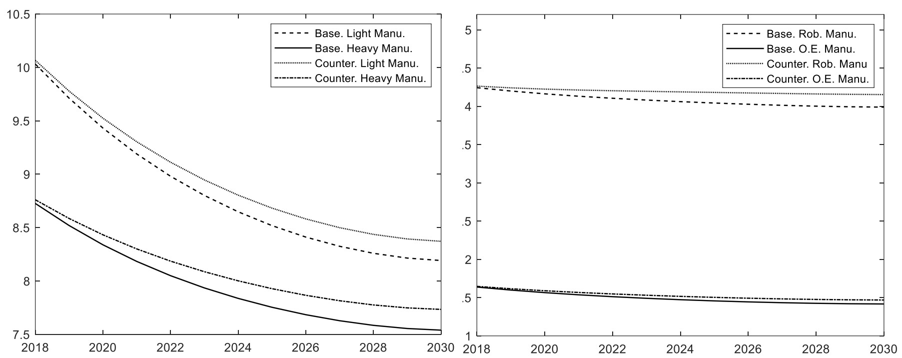


Figure3(d) Policy simulation 2: Firm migration rate in West

Figure3 Firm migration rate in various scenarios

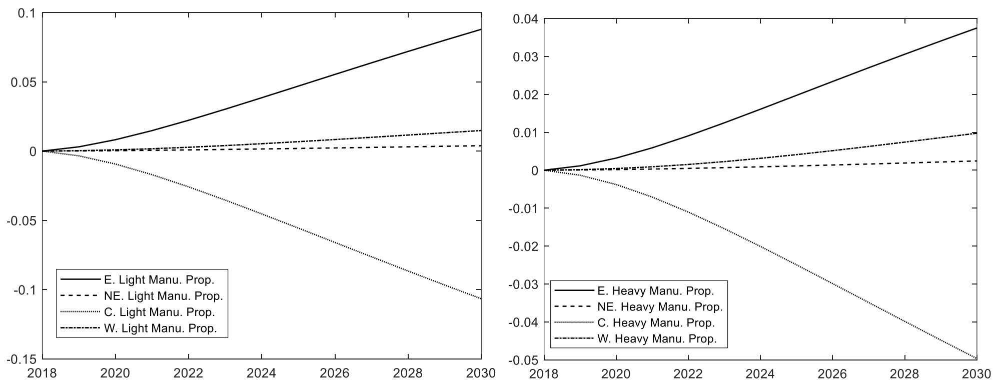
3.5 The Stock of Manufacturing Firms

In this subsection, we use the manufacturing share of each province to investigate the stock of manufacturing firms. The change in the share of firms in various manufacturing sectors in each region under four scenarios (the difference between the policy change and before the change) is shown in Figure 4. Taking the policy simulation scenario 2 in western provinces increasing the robot procurement subsidy by 15% as an example (Figure 4(d)), if western provinces increases the robot subsidy by 15%, the share of light industry in eastern provinces will decrease by 0.08%, approximately adding 1,554 firms, the Northeast will increase by 0.005%, approximately adding 929 firms, central provinces will decrease by 0.16%, approximately reducing 6,259 firms, and western provinces will increase by 0.23%, approximately adding 13,849 firms; the share of heavy industry in eastern provinces will decrease by 0.06%, approximately adding 1,306 firms, the

Northeast will increase by 0.0009%, approximately adding 314 firms, central provinces will decrease by 0.15%, approximately reducing 3,371 firms, and western provinces will increase by 0.21%, approximately adding 7,300 firms; the share of robot industry in eastern provinces will decrease by 0.03%, approximately adding 414 firms, the Northeast will increase by 0.0002%, approximately adding 52 firms, central provinces will decrease by 0.14%, approximately reducing 2,076 firms, and western provinces will increase by 0.17%, approximately adding 2,689 firms; the share of other equipment manufacturing in eastern provinces will decrease by 0.008%, approximately adding 857 firms, the Northeast will increase by 0.004%, approximately adding 53 firms, central provinces will decrease by 0.17%, approximately reducing 906 firms, and western provinces will increase by 0.18%, approximately adding 1,249 firms. Overall, western provinces increasing the robot subsidy will cause the share of manufacturing firms in western provinces to increase nationwide, while the share of manufacturing firms in the central and eastern regions will decrease, with central provinces's share decreasing more relatively.

In addition, Figure 4 also reveals the potential spatial dynamics of Chinese firms under the background of robots, presenting a "gradient transfer" characteristic: when manufacturing firms in central provinces relocate, they mainly flow back to eastern provinces (Figure 4(a)); the negative impact of policy shocks on eastern provinces is relatively small (Figure 4(b)); central provinces mainly attracts firms from eastern provinces (Figure 4(c)), and western provinces mainly attracts firms from central provinces (Figure 4(d)). Combining Figures 4(a) and 4(c), central provinces has a larger dependence on eastern provinces: firms that move out mainly flow back to eastern provinces, and firms that move into central provinces also mainly come from eastern provinces. This is because eastern provinces has a larger manufacturing industry scale, and when the nearby region is positively impacted, its larger sector scale and local competition pressure drive a large number of firms to move to the region; when the nearby region is negatively impacted, it relies on the supply chain cost advantage shaped by the industry scale to build a strong profit prospect, attracting firms from nearby regions. From Figure 4(b), the negative impact of policy shocks on eastern provinces is relatively small, and the supply chain cost advantage created by the larger industry scale in eastern provinces plays a key role, possessing strong firm rootedness and economic resilience. Finally, from Figure 4(d), due to the smaller industry scale in central provinces compared to eastern provinces and the relatively weak supply chain support, the impact is greater than the same-industry competition pressure in eastern provinces, leading to western provinces mainly attracting firms relocating from central provinces.

It should be noted that we have not yet considered the impact of the existing upstream and downstream association stickiness of firms (Carvalho and Voigtländer, 2014), so it may underestimate the "gradient transfer" characteristic in fact.



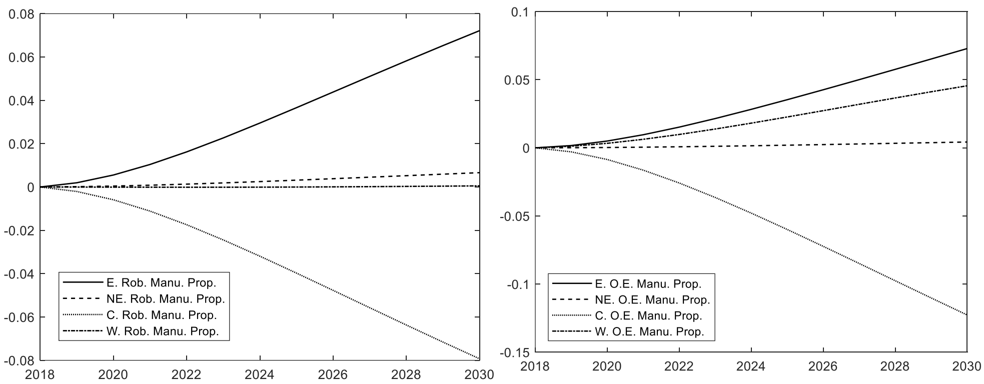


Figure4(a) Counterfactual 1: Proportion of firms across various manufacturing sectors

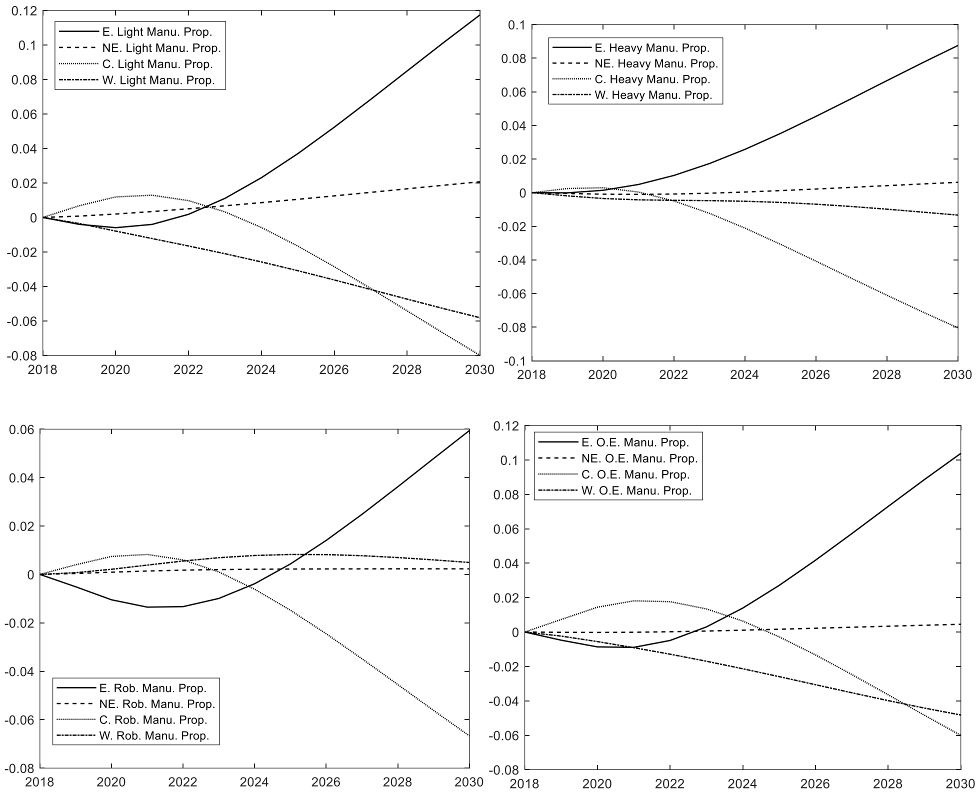
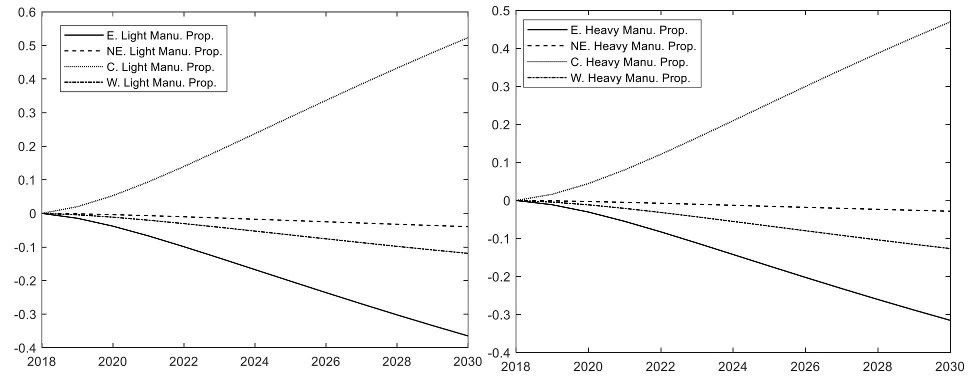


Figure4(b) Counterfactual 2: Proportion of firms across various manufacturing sectors



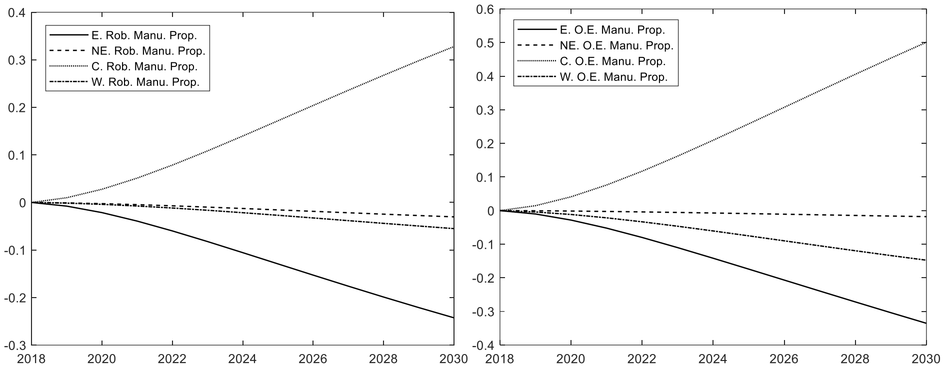


Figure4(c) Policy Simulation 1: Proportion of firms across various manufacturing sectors

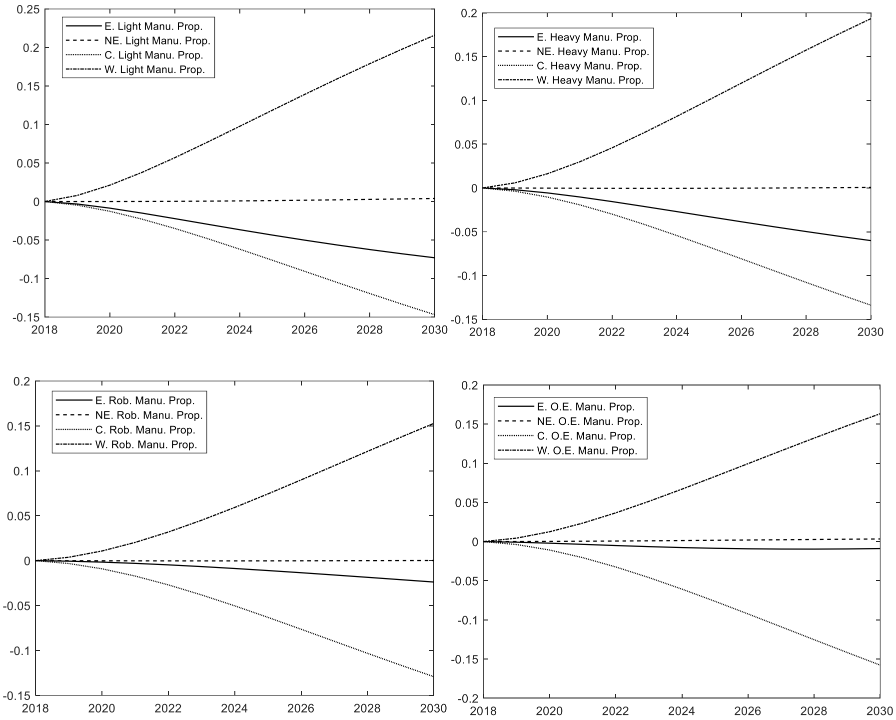


Figure4(d) Policy Simulation 2: Proportion of firms across various manufacturing sectors

Figure4 Changes in the proportion of firms in each manufacturing sector

3.6 Regional Labor Distribution

In addition to affecting the entry and exit and spatial layout dynamics of firms, the robot procurement subsidy policy will also affect the total expected utility of various regions, thereby affecting the labor layout. Figure 5 shows the related results. From Figure 5(a), after Anhui cancels the robot procurement subsidy policy, the labor share in the eastern and western regions increases, while the labor share in central provinces decreases. This result seems counterintuitive at first glance. Under the premise that we do not include the "job creation effect" of automation technology in the model, reducing the robot use subsidy actually leads to a decrease in the local labor share. The reason is that our counterfactual simulation considers the spatial layout decision of firms. When Anhui cancels the robot subsidy, the firms deployed in the area face a decline in expected total profits, so some firms are lost, and some labor demand is also lost. The wage decline caused by the firm relocation and labor demand decline exceeds the substitution effect generated by "replacing people with machines". This is similar to the conclusions of existing studies. Wang and Dong (2020) found that robots reduced the labor demand at the firm level, but Chen et al. (2022) did not find a significant decline in employment rates at the city level. The reason may be that the firm's entry and exit dynamics at the national level leads to changes in labor demand. We provide evidence at the regional level that robots affect the local expected utility through the extensive margin of labor demand and attracts labor migration. It should be noted that we still found evidence that robots attract labor migration without including the "job creation effect" described by Acemoglu and Restrepo (2018), so it may underestimate the real attraction of labor migration.

Figure 5(b) shows that the robot procurement subsidy in eastern provinces did not significantly affect the change in labor shares in various regions. This also verifies the findings in Figures 3 and 4, that is, the robot procurement subsidy in eastern provinces has a small impact on the spatial layout of firms, and thus does not lead to changes in labor shares in various regions. Similarly, Figures 5(c) and 5(d) can be analyzed. When the central and western regions increase the robot procurement subsidy by 15%, the labor share in the corresponding regions rises, and the labor share in other regions decreases. Among them, when central provinces increases the robot procurement subsidy by 15%, the labor share will increase by 3.61% by 2030, and the labor shares in the eastern, northeastern, and western regions will decrease by 1.3%, 0.17%, and 2.13% respectively; when western provinces increases the robot procurement subsidy by 15%, the labor share will increase by 2.01% by 2030, and the labor shares in the central, eastern, and northeastern regions will decrease by 1.31%, 0.66%, and 0.04% respectively. Comparing Figures 5(c) and 5(d), the robot subsidy in central provinces leads to a faster decrease in the labor share in eastern provinces, which is caused by the inter-regional migration cost. It should be noted that the labor migration into the central and western regions after the robot subsidy increase is driven by the increase in expected utility (welfare), which will be described in the next section.

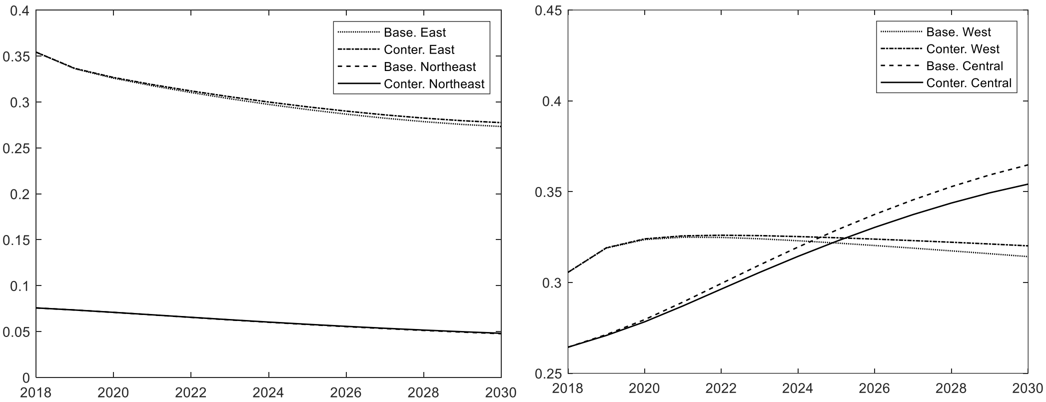


Figure5(a) Counterfactual 1: Proportion of labor force across different regions

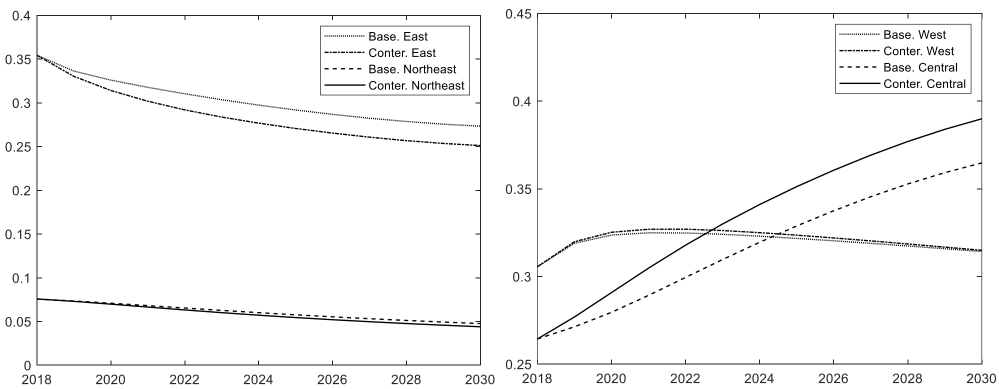


Figure5(b) Counterfactual 2: Proportion of labor force across different regions

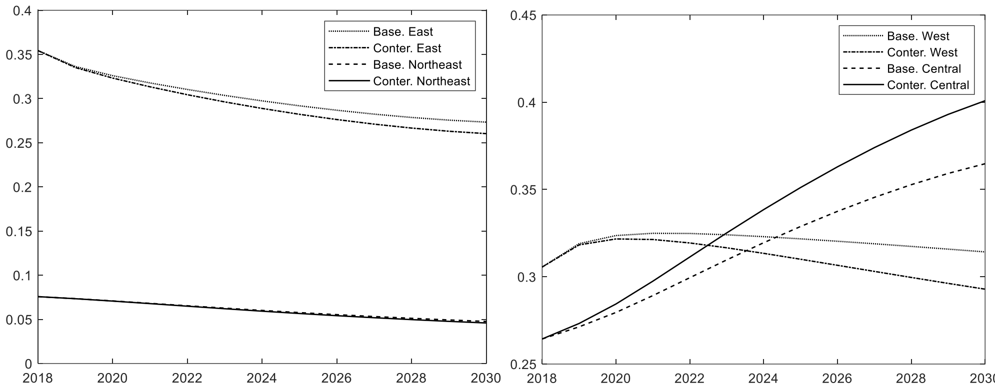


Figure5(c)Policy Simulation 1: Proportion of labor force across different regions

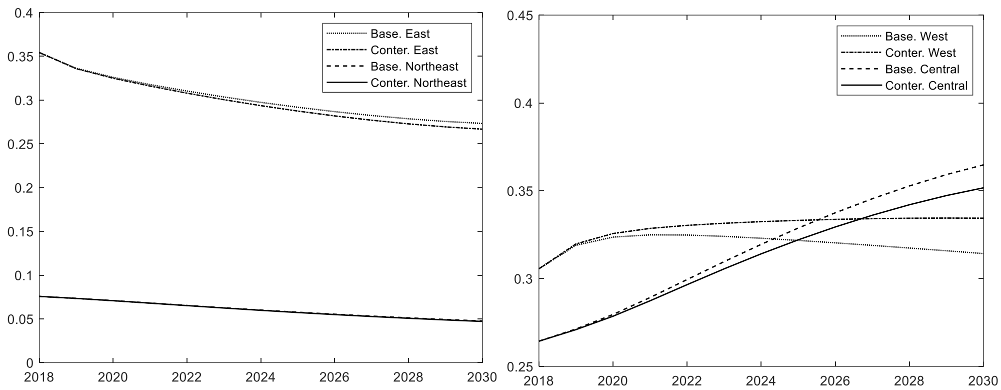


Figure5(c)Policy Simulation 2: Proportion of labor force across different regions

Figure 5 Changes in the proportion of the national labor force

3.7 Welfare Analysis

Referring to Caliendo et al. (2019) to construct the welfare expression of the household sector,

$$\widehat{W}^n = \sum_{s=1}^{\infty} \beta^s \log\left(\frac{\hat{C}_s^n}{\left(\hat{\mu}_t^{n,n}\right)^{v}}\right)$$

The welfare at the national and regional levels is weighted by the labor shares of each region in the base period. In addition, we also calculate the welfare change without conversion costs. The calculation method is to take the utility of the household sector in the steady-state equilibrium as the utility obtained by each period. This result can depict the expected utility of each region under the steady-state equilibrium, that is, the utility that the household sector can obtain in the long-term equilibrium of a certain region; at the same time, it can reflect the welfare impact of the dynamic adjustment process between equilibria, that is, the additional welfare gains and losses in the convergence process to the long-term equilibrium. The results are shown in Table 3.

Table 3 shows the changes in residents' welfare under various scenarios. Under counterfactual scenario 1, after Anhui cancels the robot procurement subsidy, the welfare of the whole country decreases (the national level decreases by 1.6142%). In central provinces, the aggregate welfare loss is smaller than the long-run welfare loss, and the reason is that when the robot subsidy is cancelled, “replacing people with machines” leads to an increase in labor demand and wage improvement, but as firms relocate, labor demand decreases. The final welfare loss in the long-term equilibrium (-1.0023%) is greater than the aggregate welfare loss (-0.8151%). Long-run welfare losses in other regions are all smaller than the aggregate welfare losses, and the reason is that the entry of firms promotes labor demand, and the increase in wages leads to a decrease in welfare losses in the long-term equilibrium. Under counterfactual scenario 2, the impact of canceling the robot procurement subsidy in eastern provinces is relatively small. The aggregate welfare of the country increases by 0.0533%, and the aggregate welfare in eastern provinces increases by 0.3757%, mainly due to the “replacing people with machines” factor, but the welfare gain in the long-term equilibrium is small (only 0.0090%). Other regions suffer welfare losses in the short term, due to the supply chain transmission effect caused by the increase in production costs in eastern provinces; in the long term, they receive firms flowing out from eastern provinces, generating welfare gains. Comparing the two counterfactual scenarios, the robot procurement subsidy in central provinces (Anhui) has a greater welfare benefit at the national level and is more necessary.

In policy simulation scenario 1, after central provinces increases the robot procurement subsidy by 15%, the aggregate welfare of the country increases by 4.4800%, and the long-term welfare increases by 3.0464%. Central provinces suffer from the impact of “replacing people with machines” in the short term, and the actual wage decreases and welfare is damaged (-0.9031%), but in the long term, it can attract firms to enter, and the welfare gain in the long-term equilibrium is 3.7149%, which is consistent with the analysis in the previous section, that is, encouraging the use of robots will attract firms to enter, although it has a negative impact on welfare in the short term, but the welfare gain in the long-term equilibrium is positive. The aggregate welfare and long-run welfare in other regions have positive gains, which come from the supply chain spillover effect of the decline in basic input element costs (specific analysis is in the next section); and the welfare gain in the long-term equilibrium is smaller than the aggregate welfare change, because central provinces’ robot procurement subsidy leads to firms flowing to central provinces.

Policy simulation scenario 2 is similar to policy simulation scenario 1, with the difference being the policy occurrence and aggregate welfare loss areas becoming western provinces. Comparing the results of policy simulation 1 and policy simulation 2, compared with western provinces, the robot procurement subsidy in central provinces can produce more obvious welfare gains, which is due to the closer supply chain association between central provinces and the eastern and northeastern regions, and the larger supply chain spillover effect of the basic input element costs.

Table3 Welfare Analysis

Region		Counterfactual1	Counterfactual2	Policy Sim. 1	Policy Sim. 2
Eastern Provinces	Welfare change	-2.6103%	0.3757%	8.0958%	2.6238%
	Long-run Welfare	-0.7926%	0.0090%	2.5962%	0.3996%
Central Provinces	Welfare change	-0.8151%	-0.1997%	-0.9031%	1.7224%
	Long-run Welfare	-1.0023%	0.0452%	3.7149%	0.3310%
Western Provinces	Welfare change	-1.0084%	-0.1421%	4.1809%	-0.1287%
	Long-run Welfare	-0.9851%	0.0381%	3.0491%	0.9077%

Northeast Provinces	Welfare change	-1.1207%	-0.1271%	4.1966%	0.9724%
	Long-run Welfare	-1.0081%	0.0272%	3.2057%	1.0578%
China	Welfare change	-1.6142%	0.0533%	4.4800%	1.5325%
	Long-run Welfare	-0.9136%	0.0273%	3.0464%	0.5693%

4. Driving forces of Firm Dynamics

4.1 Competition Effect, Supply Chain Spillover, and Factor Cost Effect

Due to the competition effect and supply chain association between various regions and sectors, the spatial layout and entry and exit of firms may produce a "snowball" effect, expanding the impact of the shock (Baqaee, 2018; Acemoglu and Tahbaz-Salehi, 2020). This part of the research is mostly focused on the production network literature, and we draw on it, decomposing the driving factors of firm spatial layout into competition effect, supply chain spillover, and factor cost effect in the dynamic spatial general equilibrium model. Specifically, the robot procurement subsidy directly affects the factor costs faced by firms, and firms then decide on entry and exit and spatial layout decisions. The decisions of firms will affect the scale of various industrial sectors in the macro, which on the one hand affects the profits of local firms in the same sector through local competition, and on the other hand affects the intermediate input costs and profits of firms engaged in production through the supply chain cost spillover effect (see equation (7) and intermediate goods ideal price index), and the two effects continue to expand the impact of robot procurement subsidies on firm spatial layout and industrial sector scale. In this way, the impact continues to expand, and a simple schematic diagram is shown in Figure 6.

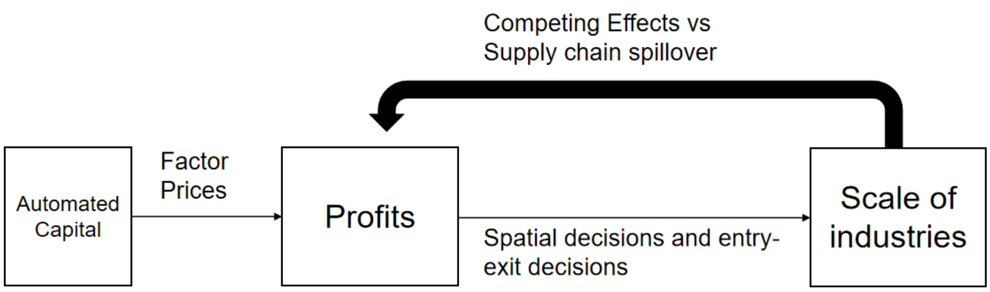


Figure 6 Effect decomposition and logical chain of driving factors of firm spatial layout

To further explore the effect decomposition and logical chain shown in Figure 6, assume that the region n introduces a subsidy policy for robots in period 0 (this situation is denoted with a superscript "′"), then the robot price of firms will be lower than the original path $\theta_A^{\prime nj} < \theta_A^{nj}$, so the adjustment effect of robots generated thereby is recorded as $d\log\left(1-\theta_A^{nj}\right)/d\log s^{m,n}$. We focus on the key variable of profit, which affects the dynamic changes in the relative profits of firms in a certain region.

Let the profit obtained by the firm from the region i be $\pi_t^{nj,i} = \frac{1}{\sigma^j-1}\frac{x_t^{nj}}{a^{nj}}\left(q_t^{nj,i}\right) = \frac{\lambda_t^{nj,i} X_t^{ij}}{M_t^{nj}\sigma^j}$.

Define the ratio of robots use to added value as $\lambda_t^{m,nj} = \frac{(1-s^{m,n})P_t^{m,n} m_t^{nj}}{p_t^{va,nj} va_t^{nj}} = \left(1 - \theta_A^{nj}\right)\left(\frac{(1-s^{m,n})P_t^{m,n}}{p_t^{va,nj}}\right)^{1-\zeta}$, here due to $\zeta > 1$, the decline in the price of robots $P_t^{m,n}$ leads to an increase in its demand. Therefore, when the local introduces a subsidy policy for robots, it will lead to an increase in $\lambda_t^{m,nj}$. To avoid the interference of endogenous factors other than robots, we adopt an analysis method similar to "difference-in-differences" to study the relative profit changes of firms in a certain region caused by changes in robots.

Specifically, the profit ratio of firms in region n relative to region l (or foreign) is $\frac{\pi_t^{nj,i}}{\pi_t^{lj,i}} = \frac{\lambda_t^{nj,i}/\lambda_t^{lj,i}}{M_t^{nj}/M_t^{lj}}$, combined with equation (29), there is

$$\frac{d\log \pi_t^{nj,i}/\pi_t^{lj,i}}{d\log s^{m,n}} = \left(1-\sigma^j\right)\left[\frac{d\log x_t^{nj}}{d\log s^{m,n}} - \frac{d\log x_t^{lj}}{d\log s^{m,n}}\right] \tag{35}$$

According to the unit cost of firm inputs obtained from equation (15),

$$\frac{d\log x_t^{nj}}{d\log s^{m,n}} = \gamma^j \frac{d\log p_t^{va,nj}}{d\log s^{m,n}} + \sum_{k=1}^{J} \gamma^{k,j} \frac{d\log P_t^{nk}}{d\log s^{m,n}} \tag{36}$$

We define a share matrix $\boldsymbol{\Lambda}_t$ of dimension $NJ \times NJ$, where $\boldsymbol{\Lambda}_t^{ik,nj} = \frac{\gamma^{k,j} M_t^{ik}\left(p_t^{ik,n}\right)^{1-\sigma^k}}{\left[\sum_{h=1}^{N} M_t^{hk}\left(p_t^{hk,n}\right)^{1-\sigma^k}\right]}$ is the share of products from upstream region i, sector k to downstream region n, sector j, the $NJ \times NJ$ unit matrix is $\boldsymbol{I}$, then the inverse matrix $\boldsymbol{L}_t' = (\boldsymbol{I} - \boldsymbol{\Lambda}_t')^{-1} = \boldsymbol{I} + \boldsymbol{\Lambda}_t' + (\boldsymbol{\Lambda}_t')^2 + \cdots$ characterizes the sum of direct, indirect, and higher-order indirect effects between different regions and sectors. Let the total impact of region i, sector j to downstream region n, sector j be $\boldsymbol{L}_t^{ik,nj}$, which can be summarized as Proposition 1.

Proposition 1 When the region n introduces a subsidy policy for robots in period 0, the impact of local firm production costs can be summarized as firm layout effect and general equilibrium effect (in sector j):

$$\frac{d\log x_t^{nj}}{d\log s^{m,n}} = \sum_{g=1}^{N}\sum_{h=1}^{J} \boldsymbol{L}_t^{gh,nj} \gamma^h \frac{d\log p_t^{va,gh}}{d\log s^{m,n}} + \boldsymbol{L}_t^{gh,nj} \sum_{k=1}^{J}\sum_{i=1}^{N} \frac{\gamma^{k,h} M_t^{ik}\left(p_t^{ik,g}\right)^{1-\sigma^k} \frac{d\log M_t^{ik}}{d\log s^{m,n}}}{\left(1-\sigma^k\right)\left[\sum_{u=1}^{N} M_t^{uk}\left(p_t^{uk,g}\right)^{1-\sigma^k}\right]} \tag{37}$$

In equation (37) of Proposition 1, $\frac{d\log M_t^{ik}}{d\log s^{m,n}}$ represents the firm layout effect of the region n's robot subsidy on the firms in region i, sector k, and its impact is transmitted to the region n sector j through inter-regional trade shares $\boldsymbol{\Lambda}_t^{ikgh}$ and supply chain effects $\boldsymbol{L}_t^{gh,nj}$. $\frac{d\log p_t^{va,gh}}{d\log s^{m,n}}$ represents the general equilibrium effect of the region n's robot subsidy on the region g sector h, represented by composite factor prices, and its impact is transmitted to region n sector j through the added value share of γ^h and the supply chain effect $\boldsymbol{L}_t^{gh,nj}$.

On the basis of Proposition 1, equation (35) can be further decomposed into the firm layout effect and general equilibrium effect of each region and sector, which is summarized as Proposition 2. The specific proof is in our Appendices.

Proposition 2 After the robot subsidy policy is implemented, the relative profit of the firm in the region n sector j compared to the region l can be decomposed into the firm competition effect of the local sectors, the supply chain association effect of other sectors in the local region, the competition effect of other sectors in other regions, the supply chain spillover effect of other sectors in other regions, and the factor price effect.

$$d\log \pi_t^{nj,i}/\pi_t^{lj,i} = \left(1-\sigma^j\right)\left[dM_t^n(nj,lj,ij) + \sum_{g\neq n} dM_t^g(nj,lj,ij) + \sum_{g=1}^{N} dva_t^g(nj,lj,ij)\right] \quad (38)$$

In the decomposition of Equation (38) by region, the local firm layout effect, that is, the impact of robot subsidies on the relative profits of sales of sector j 's products from region n to region i, by affecting the number of firms engaged in production in the region. Specifically, it includes the competition effect of local firms in this sector and the supply chain spillover effect of other sectors in the region.

$$\begin{aligned} dM_t^n(nj,lj,ij) = {} & \underbrace{\left(\boldsymbol{L}_t^{nj,nj} - \boldsymbol{L}_t^{nj,lj}\right)\sum_{k=1}^{J}\sum_{i=1}^{N}\frac{\gamma^{k,j}M_t^{ik}\left(p_t^{ik,n}\right)^{1-\sigma^k}}{\left(1-\sigma^k\right)\left[\sum_{u=1}^{N}M_t^{uk}\left(p_t^{uk,n}\right)^{1-\sigma^k}\right]}d\log M_t^{ik}}_{\text{The peer competition effect}} \\ & \underbrace{+\sum_{h\neq j}\left(\boldsymbol{L}_t^{nh,nj} - \boldsymbol{L}_t^{nh,lj}\right)\sum_{k=1}^{J}\sum_{i=1}^{N}\frac{\gamma^{k,h}M_t^{ik}\left(p_t^{ik,n}\right)^{1-\sigma^k}}{\left(1-\sigma^k\right)\left[\sum_{u=1}^{N}M_t^{uk}\left(p_t^{uk,n}\right)^{1-\sigma^k}\right]}d\log M_t^{ik}}_{\text{the supply chain spillover effect in the region}} \end{aligned} \quad (39)$$

The spillover effect of firm layout in other regions, that is, the impact of robot subsidies on the relative profits of sales of sector j's products from region n to region i by affecting the number of firms engaged in production in other regions. Its impact can also be broken down into spillover effects from the sector in other regions and supply chain spillover effects from other sectors in other regions.

$$\begin{aligned} dM_t^g(nj,lj,ij) = {} & \underbrace{\left(\boldsymbol{L}_t^{gj,nj} - \boldsymbol{L}_t^{gj,lj}\right)\sum_{k=1}^{J}\sum_{i=1}^{N}\frac{\gamma^{k,j}M_t^{ik}\left(p_t^{ik,g}\right)^{1-\sigma^k}}{\left(1-\sigma^k\right)\left[\sum_{u=1}^{N}M_t^{uk}\left(p_t^{uk,g}\right)^{1-\sigma^k}\right]}d\log M_t^{ik}}_{\text{Spillover effects from the sector in other regions}} \\ & \underbrace{+\sum_{h\neq j}\left(\boldsymbol{L}_t^{gh,nj} - \boldsymbol{L}_t^{gh,lj}\right)\sum_{k=1}^{J}\sum_{i=1}^{N}\frac{\gamma^{k,h}M_t^{ik}\left(p_t^{ik,g}\right)^{1-\sigma^k}}{\left(1-\sigma^k\right)\left[\sum_{u=1}^{N}M_t^{uk}\left(p_t^{uk,g}\right)^{1-\sigma^k}\right]}d\log M_t^{ik}}_{\text{Spillover effects from other sectors in other regions}} \end{aligned} \quad (40)$$

The factor price effect in region g, that is, the impact of robot subsidies on the relative profits of region n from selling sector j's products to region i by affecting factor prices in each region is:

$$dva_t^g(nj,lj,ij) = \sum_{h=1}^{J}\left(\boldsymbol{L}_t^{gh,nj} - \boldsymbol{L}_t^{gh,lj}\right)\gamma^h d\log p_t^{va,gh} \quad (41)$$

4.2 Numerical Decomposition Results

This section focuses on the impact of policy changes on the relative profits of local firms.

The dynamic effect decomposition results under counterfactual scenario 1 are shown in Figure 7. From the figure, the competition effect of the local sector and the supply chain association effect of other sectors in the local region play a leading role. From the perspective of the net impact of factor prices, the net impact of factor prices on the relative profits of the four manufacturing sectors in Anhui is small and mainly affects light industry and heavy industry (-0.63% and -0.20%), and the factor price effect of robot equipment manufacturing is positive, mainly because this sector is the supplier of robots. From the local effect perspective, after the robot procurement subsidy is cancelled, due to firm relocation, the competition pressure faced by the four manufacturing sectors decreases, resulting in profit increases of 2.00%, 4.80%, 1.33%, and 1.61% respectively; similarly, due to firm relocation, the decline in other sectors in the local region and the rise in intermediate prices lead to a negative supply chain association effect, which are -1.81%, -1.80%, -2.57%, and -2.73% respectively. From the perspective of other regions, the supply chain spillover effect of other sectors in other regions exceeds the trade competition effect, but the overall impact is weaker than the competition alleviation effect of the local sector (0.15%, 0.59%, 0.14%, and 0.61% respectively). The supply chain spillover effect of other sectors in other regions is negative, which indicates that other sectors in other regions have a supply chain spillover effect on local firms, and compress the profits of local firms through trade competition, but this mechanism is more indirect, so it is smaller than the supply chain association effect of other sectors in the local region, which are -0.12%, -0.07%, -0.08%, and -0.09% respectively.

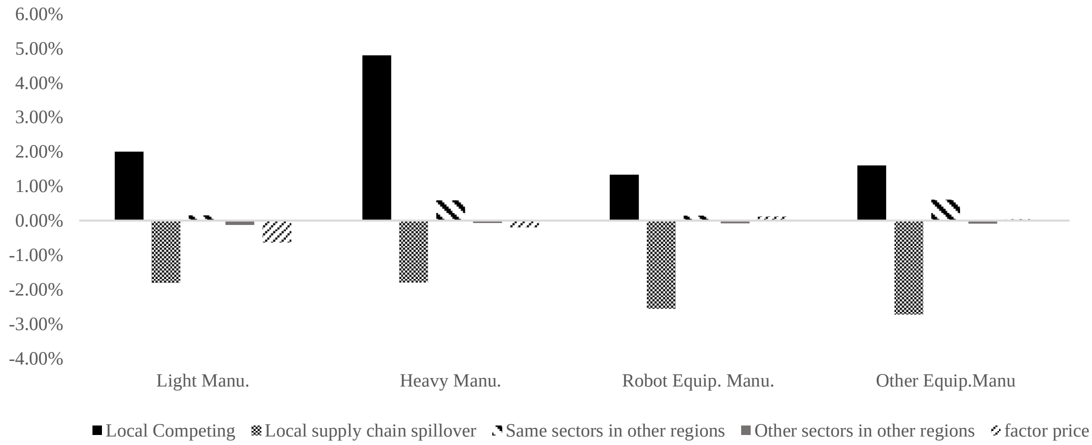
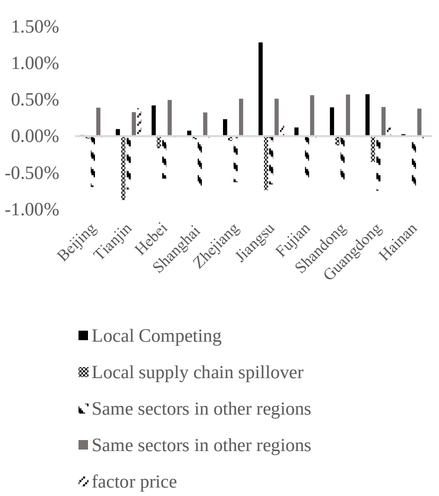
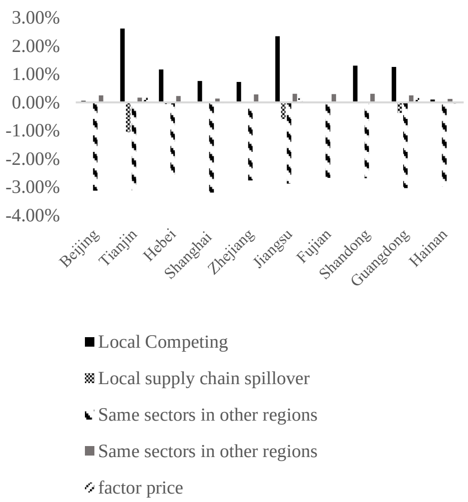


Figure 7 Decomposition of dynamic effects in Anhui in Counterfactual 1

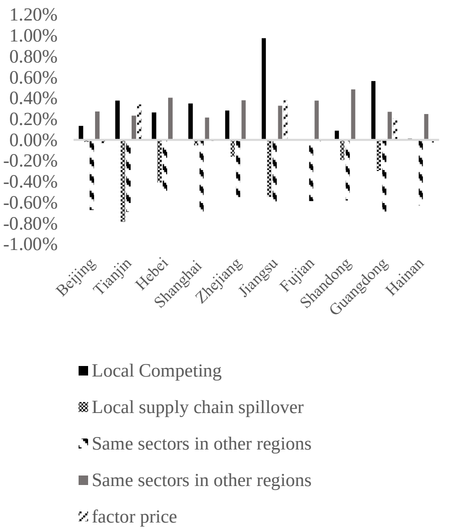
The dynamic effect decomposition results under counterfactual scenario 2 are shown in Figure 8, where the main negative impact comes from the trade competition effect of other sectors in other regions and the supply chain association effect of other sectors in the local region; the main positive impact comes from the alleviation of competition pressure in the local sector. From the perspective of the net impact of factor prices, the negative impact of the robot procurement subsidy on light and heavy industries is lower than that under counterfactual scenario 1, and the impact on most regions' robot equipment and other equipment sectors is smaller than that under counterfactual scenario 1, which indicates that the supply chain in eastern provinces can alleviate the impact of negative policy shocks to a certain extent, but at the same time, the internal industry scale and supply chain association heterogeneity are relatively strong. From the local effect perspective, the two local effects in most regions are weaker than those under counterfactual scenario 1, and the symbols are the same, which indicates that the larger industry scale in eastern provinces has created a strong supply chain cost advantage, which can maintain the relative profits of firms and has strong rootedness and economic resilience. The scale of the two effects in other regions is larger than that under counterfactual scenario 1 and the symbols are opposite, which indicates that the main factors affecting the profits of manufacturing firms in eastern provinces are not from the local area. After the three eastern regions cancel the robot procurement subsidy, on the one hand, they increase the firms in other sectors in other regions, compressing the profits of manufacturing firms in eastern provinces through trade competition effects; on the other hand, they also increase the firms in other sectors in other regions, and the supply chain spillover effect generated in eastern provinces is greater than that on local firms, thus raising the profit level of eastern provinces. Figure 8 shows that the local impact of policy shocks in eastern provinces is relatively small, which verifies the conclusion of Figure 4, but it will also have indirect impacts on other regions.



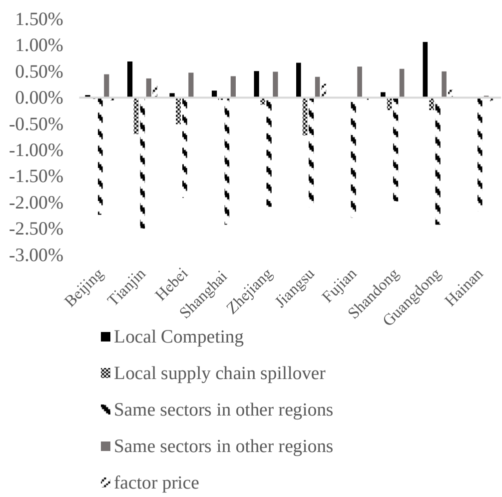
Light Manu.



Heavy Manu.



Robot Equip. Manu.

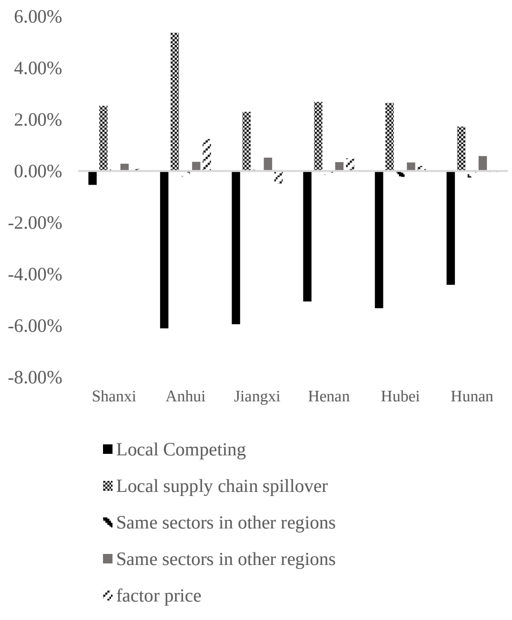


Other Equip. Manu.

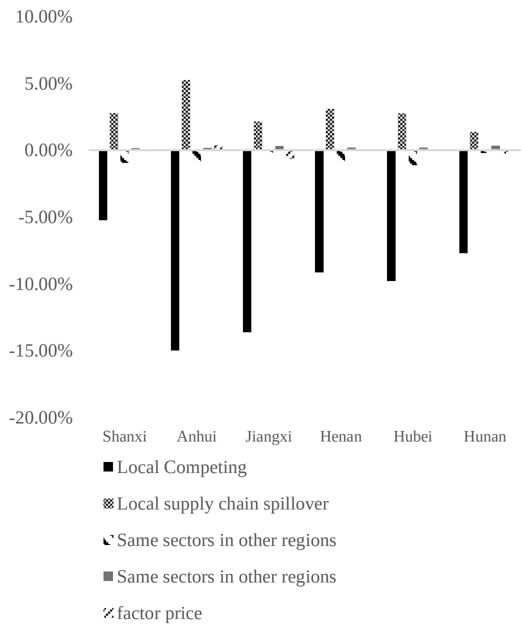
Figure 8 Decomposition of dynamic effects in the eastern provinces in Counterfactual 2

The dynamic effect decomposition results under policy simulation scenario 1 are shown in

Figure 9, where the competition effect of the local sector (negative) and the supply chain association effect of other sectors in the local region (positive) play a leading role. From the perspective of the net impact of factor prices, the subsidy policy reduces the relative profits of most regions in central provinces's heavy industry, robot equipment, and other equipment sectors, mainly because the large-scale entry of firms has pushed up the price of robots, leading to a decline in profits. From the perspective of the competition effect of the local sector, the policy leads to intensified competition and profit decline in various manufacturing sectors. The decline is the fastest in heavy industry (an average of 10.09%), which indicates that the original number of heavy industries in central provinces is relatively small compared to the light industry sector, and the number of new firms attracted is larger compared to the two equipment manufacturing sectors, so the competition pressure increases and the profits are "spread thin"; and the declines in Anhui and Jiangxi are the largest, reaching 14.99% and 13.63% respectively, indicating that the two places have attracted the most heavy industry firms. From the perspective of the supply chain association effect of other sectors in the local region, the robot procurement subsidy promotes the entry of new firms in various sectors in the local region, lowering the price of intermediate goods and raising the profit level of various sectors. Among them, the local supply chain association effect in Anhui Province is the most obvious, reaching 5.36%, 5.25%, 7.83%, and 8.29% respectively, which shows that the local supply chain in Anhui Province further amplifies the incentive effect of the policy. From the perspective of the spillover effect of other sectors in other regions, the symbols of various regions are different, that is, the trade competition effect and the supply chain spillover effect are "mutually victorious and defeated", and only the supply chain spillover effect of other equipment manufacturing sectors exceeds the trade competition effect. From the perspective of the supply chain spillover effect of other sectors in other regions, various regions have obtained positive profit benefits, which shows that central provinces is supported by the national supply chain, which helps to enhance the positive effect of the policy.



Light Manu.



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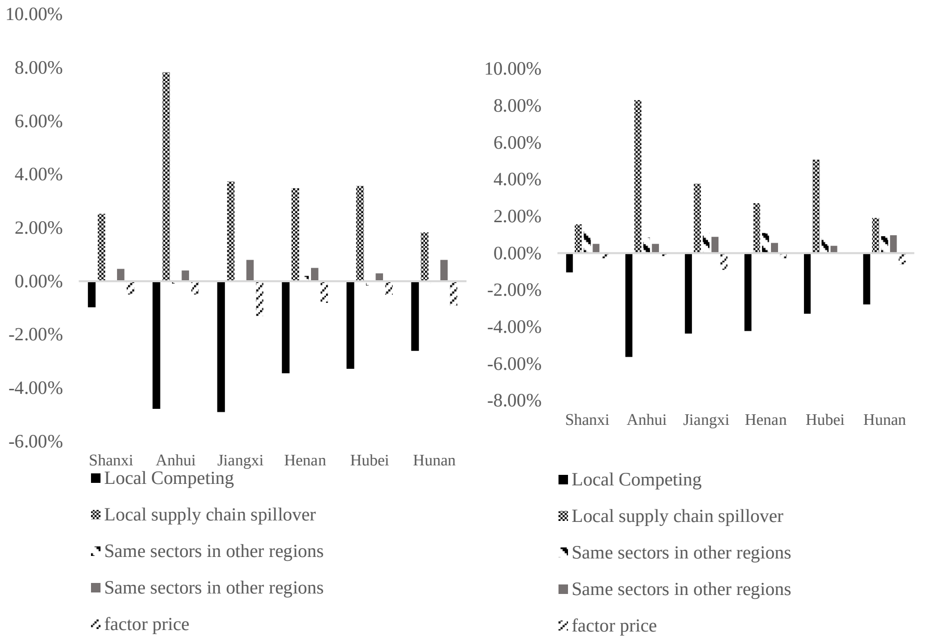
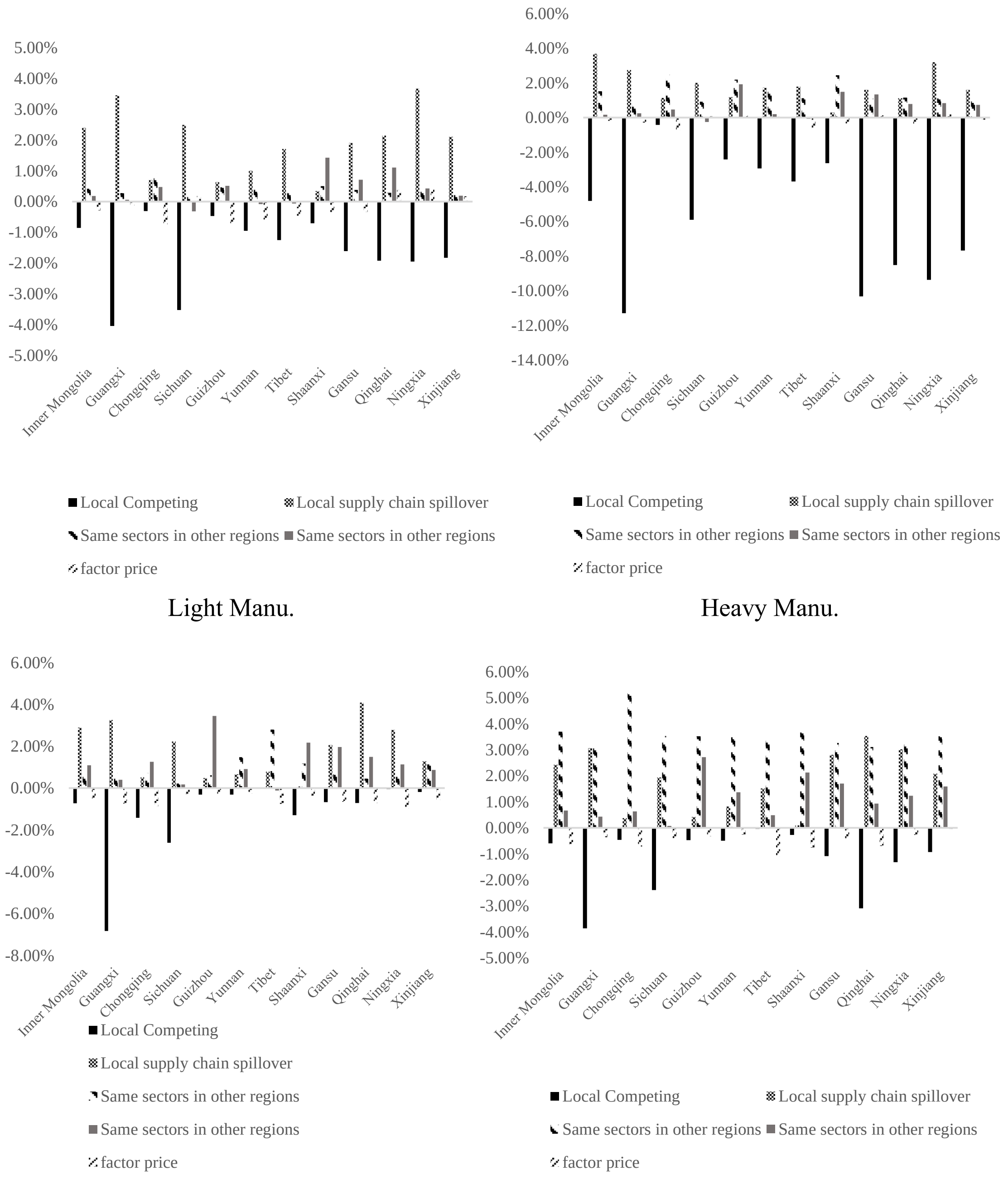


Robot Equip. Manu. Other Equip. Manu.

Figure 9 Decomposition of dynamic effects in the central provinces in Policy Simulation 1

The dynamic effect decomposition results under policy simulation scenario 2 are shown in Figure 10, where the competition effect of the local sector (negative) and the supply chain association effect of other sectors in the local region (positive) play a leading role in most sectors, and the main positive role is played by other sectors in other regions. From the perspective of the net impact of factor prices, the subsidy policy reduces the relative profits of most regions in western provinces, and the reasons are similar to those in policy simulation scenario 1. The competition effect of the local sector is similar to that in policy simulation scenario 1, and the decline is the fastest in heavy industry (an average of -5.83%), and the declines in Guangxi and Gansu are the largest, reaching -11.30% and -10.33% respectively, and the potential reasons are similar to those in policy simulation scenario 1. From the perspective of the supply chain association effect of other sectors in the local region, the robot procurement subsidy raises the profit level of various sectors in western provinces. From the perspective of the spillover effect of other sectors in other regions, this shows that the supply chain spillover effect of other sectors in western provinces exceeds the trade competition effect, especially in other equipment manufacturing sectors (an average impact of 3.57%). From the perspective of the supply chain spillover effect of other sectors in other regions, most regions and sectors have obtained positive profit benefits, that is, western provinces is supported by the national supply chain, which helps to enhance the positive effect of the policy.

Comparing the two policy simulation scenarios, if considering the robot procurement subsidy policy, the role of central provinces is greater than that of western provinces, especially in heavy industry, robot equipment manufacturing, and other equipment manufacturing sectors. The welfare analysis in Table 3 has given a similar judgment, and this is further confirmed from the perspective of firm profits.



Light Manu.

Heavy Manu.

Robot Equip. Manu.

Other Equip. Manu.

Figure 10 Decomposition of dynamic effects in the western provinces in Policy Simulation 2

5. Conclusions

Macro data show that robots has the effect of attracting firms to enter and layout and enhancing the rootedness of firms; existing literature also shows that robots reduce the labor demand at the firm level, but no significant decline in employment rates or inclusive growth levels has been found at the regional level. The above facts all show that robots cause extensive marginal changes in firm spatial dynamics, and has obvious effects at both macro and micro levels. We base our study on a dynamic quantitative spatial general equilibrium model that includes robots and firm dynamics, and explains the changes in firm spatial dynamics, labor layout, and resident welfare caused by the procurement incentives of robots in a unified theoretical framework. We find that robots not only help to enhance firm rootedness and migration rate, but also produce the characteristic of "gradient transfer": when manufacturing firms in central provinces relocate, they mainly flow back to eastern provinces; the negative impact of policy shocks on eastern provinces is relatively small; central provinces mainly attracts firms from eastern provinces, and western provinces mainly attracts firms from central provinces. In addition, we find that robots have extensive marginal effects at the dynamic spatial level: robots actually enhance local expected welfare through extensive margins and attract labor migration. Finally, the robot procurement subsidy in central provinces can produce more obvious welfare gains, which is due to the closer supply chain association between central provinces and the eastern and northeastern regions, and the larger supply chain spillover effect of basic input element costs.

The reason why the spatial layout and entry and exit of firms have such a profound impact is that the supply chain has the role of transmitting and expanding shocks, specifically including competition effect, supply chain spillover, and factor cost effect. We find that the net impact of factor prices is generally small, and the competition effect of firms in the central and western regions and the supply chain association effect of other sectors play a positive and negative leading role respectively, while the negative impact in eastern provinces comes from the trade competition effect of other sectors in other regions and the supply chain association effect of other sectors in the local region; the main positive impact comes from the alleviation of competition pressure in the local sector.

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Appendix Table1 Sector division

OECD sectors	Our division
TTL_01T02: Agriculture, hunting, forestry	
TTL_03: Fishing and aquaculture	
TTL_05T06: Mining and quarrying, energy producing products	Agriculture and Mining
TTL_07T08: Mining and quarrying, non-energy producing products	
TTL_09: Mining support service activities	
TTL_10T12: Food products, beverages and tobacco	Light Manufacture

TTL_13T15: Textiles, textile products, leather and footwear TTL_16: Wood and products of wood and cork TTL_17T18: Paper products and printing	
TTL_19: Coke and refined petroleum products TTL_20: Chemical and chemical products TTL_21: Pharmaceuticals, medicinal chemical and botanical products TTL_22: Rubber and plastics products TTL_23: Other non-metallic mineral products TTL_24: Basic metals TTL_25: Fabricated metal products	Heavy Manufacture
TTL_26: Computer, electronic and optical equipment TTL_27: Electrical equipment	Robot Equipment Manufacture
TTL_28: Machinery and equipment, nec TTL_29: Motor vehicles, trailers and semi-trailers TTL_30: Other transport equipment	Other Equipment Manufacture
TTL_31T33: Manufacturing nec; repair and installation of machinery and equipment	Other Manufacture
TTL_35: Electricity, gas, steam and air conditioning supply TTL_36T39: Water supply; sewerage, waste management and remediation activities	Services
TTL_41T43: Construction	Construction
TTL_45T47: Wholesale and retail trade; repair of motor vehicles	Wholesale and retail trades
TTL_49: Land transport and transport via pipelines TTL_50: Water transport TTL_51: Air transport TTL_52: Warehousing and support activities for transportation TTL_53: Postal and courier activities TTL_55T56: Accommodation and food service activities TTL_58T60: Publishing, audiovisual and broadcasting activities TTL_61: Telecommunications TTL_62T63: IT and other information services TTL_64T66: Financial and insurance activities TTL_68: Real estate activities TTL_69T75: Professional, scientific and technical activities TTL_77T82: Administrative and support services	Services

TTL_84: Public administration and defence; compulsory social security	
TTL_85: Education	
TTL_86T88: Human health and social work activities	
TTL_90T93: Arts, entertainment and recreation	
TTL_94T96: Other service activities	

Sectors in Chen et al. (2023)	Our division
Agriculture, Forestry, Animal Husbandry and Fishery Mining and Washing of Coal Extraction of Petroleum and Natural Gas Mining and Processing of Metal Ores Mining and Processing of Non-metal Ores	Agriculture and Mining
Manufacture of Foods and Tobacco Manufacture of Textile Manufacture of Weaing Apparel and Related Products Manufacture of Furniture and Processing Wood Manufacture of Paper Products, Printing, Sport and Entertainment Activities	Light Manufacture
Processing of Petroleum, Coking and Processing of Nuclear Fuel Chemical Industry Manufacture of Non-metallic Mineral Products Smelting and Pressing of Ferrous Metals Manufacture of Meatal Products	Heavy Manufacture
Manufacture of General Purpose Machinery Manufacutre of Special Purpose Machinery Manufacture of Transport Equipments	Other Equipment Manufacture
Manufacture of Electrical Machinery and Apparatus Manufacture of Computers, Communication and Other Electronic Equipment Manufacture of Measuring Instruments and Machinery	Robot Equipment Manufacture
Other Manufacture	Other Manufacture
Utilization of Waste Resources Repair Service of Metal Products, Machinery and Equipment Production and Supply of Electric Power and Heat Power Production and Supply of Gas Production and Supply of Water	Services

Construction	Construction
Wholesale and Retail Trades	Wholesale and retail trades
Transport,Storage and Post	Services
Hotels and Catering Services	
Information Transmission,Software and Information Technology	
Financial Intermediation	
Real Estate	
Leasing and Business Services	
Scientific Research and Technical Services	
Management of Water Conservancy,Environment and Public Facilities	
Service to Households,Repair and Other Services	
Education	
Health and Social Service	
Culture,Sports and Entertainment	
Public Management,Social Security and Social Organization	

Appendix Table 2 Estimation of $\boldsymbol{\mathcal{V}}$

	OLS				Bartik IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\beta/\mathcal{V}$	0.0453** (0.0210)	0.0453** (0.0210)	0.0581** (0.0238)	0.0542** (0.0233)	0.0292* (0.0152)	0.0317* (0.0175)	0.0317* (0.0175)
Time FE	×	√	√	√	×	×	√
Region FE	R×T	R×T	R	R	R	R	R
Sector FE	S×T	S×T	S×T	S	S	S×T	S×T
Observation	1,226	1,226	1,226	1,226	1,226	1,226	1,226

Values in parentheses are cluster standard errors; *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3 Results under varying elasticities of substitution

zeta=2

Year	Firms Prop.in Eastern provinces		Firms Prop.in Northeastern provinces		Firms Prop.in Central provinces		Firms Prop.in Western provinces	
	Model	Data	Model	Data		Model	Data	Model
2017	64.3900%	64.3900%	6.1805%	6.1805%	15.6687%	15.6687%	13.7608%	13.7608%
2018	63.7939%	63.2565%	6.1274%	6.0877%	16.1345%	16.4815%	13.9441%	14.1743%
2019	63.2898%	62.5132%	6.0795%	5.8952%	16.5611%	17.0707%	14.0695%	14.5209%
2020	62.8805%	61.8058%	6.0336%	5.6673%	16.9455%	17.6059%	14.1405%	14.9211%
2021	62.5405%	61.3751%	5.9890%	5.5601%	17.2964%	17.9450%	14.1741%	15.1198%

zeta=2.5

Year	Firms Prop.in Eastern provinces		Firms Prop.in Northeastern provinces		Firms Prop.in Central provinces		Firms Prop.in Western provinces	
	Model	Data	Model	Data		Model	Data	Model
2017	64.3900%	64.3900%	6.1805%	6.1805%	15.6687%	15.6687%	13.7608%	13.7608%
2018	63.7939%	63.2565%	6.1274%	6.0877%	16.1345%	16.4815%	13.9441%	14.1743%
2019	63.2908%	62.5132%	6.0793%	5.8952%	16.5586%	17.0707%	14.0714%	14.5209%
2020	62.8818%	61.8058%	6.0330%	5.6673%	16.9402%	17.6059%	14.1450%	14.9211%
2021	62.5409%	61.3751%	5.9879%	5.5601%	17.2897%	17.9450%	14.1815%	15.1198%