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Article

Housing Prices and Robot Adoption in Corporate Management

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Abstract

High housing prices may hinder firms from adopting labor-saving technologies, limiting opportunities for technological upgrading. This paper examines the mechanisms through which housing prices affect firms' robot adoption. Using fixed effects and two-stage least squares (2SLS) methods on data from 2000–2013, we find that a 10% increase in housing prices reduces a firm's probability of adopting robots by 1.44 percentage points. Rising housing prices decrease firms' robot adoption on the extensive margin rather than the intensive margin. The negative impact is stronger for non-state-owned firms and those highly dependent on external finance, but weaker in industries with low capital and skill intensity. Further, we find that investments outside a firm's core business crowd out robot adoption. Weak corporate governance that exacerbates managerial myopia amplifies these effects. Against the backdrop of China's overheated housing market, our findings highlight the risks that high housing prices pose to technological upgrading and underscore the importance of improved corporate governance.

Keywords: housing price; robot adoption; technology upgrading; corporate governance; managerial myopia
JEL: G32, L23, O33, R31

1. Introduction

Industrial robots constitute a critical driver of China's economic restructuring and industrial upgrading. In pursuit of high-quality development and the goal of becoming a global manufacturing powerhouse, the Chinese government has introduced a series of strategic initiatives, programs, and subsidies to foster the robotics industry. Concurrently, the arrival of the Lewis turning point has exacerbated labor shortages and escalating labor costs, compelling firms to accelerate labor-technology substitution (Du and Wei, 2022). A growing consensus suggests that while robot adoption can generate substantial benefits, unaffordable investment may expose firms to significant financial risks and indebtedness.

Since the initiation of the housing commercialization reform in 1998, China's real estate market has undergone a profound and sustained expansion. The resulting escalation in housing wealth has substantially increased firms' production, marketing, and labor costs, thereby constraining their capacity to absorb the fixed and maintenance expenditures associated with robot adoption and consequently dampening import demand. Although a considerable body of research has examined the macroeconomic and microeconomic implications of the real estate boom—particularly with respect to corporate investment, productivity, and innovation—the specific effects on firms' adoption of robots remain largely under-explored, notwithstanding the centrality of robotics to technological upgrading. This study provides a systematic assessment of how fluctuations in housing prices and firms' diversification strategies influence robot adoption within China's manufacturing sector. Moreover, by situating this relationship within the context of weak corporate governance, the study generates novel managerial implications concerning the enhancement of governance mechanisms and the strategic balance between short-term returns and long-term competitiveness through more efficient resource allocation amid China's booming property market.

Investigating the effects of housing prices on firms' robot adoption entails two principal challenges. The foremost pertains to measurement, as data provided by the International Federation of Robotics (IFR) is available only at the country-industry level and thus fails to capture firm-level variation. To address this limitation, we construct a firm-level proxy for robot adoption using Chinese customs records on robot imports. Given that the overwhelming majority of robots utilized in China between 2000 and 2013 were sourced from advanced economies such as the United States and Germany, import data constitute a widely accepted, albeit imperfect, measure of adoption, as they do not account for domestic purchases. We further merge these import records with the Annual Survey of Industrial Firms (ASIF) to a comprehensive firm-level panel dataset, enabling a systematic examination of the relationship between housing prices and robot adoption.

The second methodological challenge pertains to the potential heterogeneity of housing prices. Unobserved regional economic conditions may simultaneously influence both housing prices and firms' robot adoption decisions, po-

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tentially yielding biased and inconsistent estimates. For example, regional economic growth can elevate local housing prices while concurrently affecting the development of local import activities. To mitigate this concern, we adopt the approach proposed by Wrenn et al. (2019), employing an instrumental variable (IV) constructed from the interaction between an indicator variable—capturing whether a city's average slope exceeds the national average—and long-term loan interest rates. This interaction is positively correlated with housing construction costs and serves as a valid instrument for relative housing prices. This identification strategy is conceptually similar to that of Chaney et al. (2012) and Mian and Sufi (2011), who utilize the interaction between local housing supply elasticities and long-term interest rates. In light of limited data on city-level supply elasticities, we use geographic features that directly affect construction costs as a proxy for housing supply constraints.

Both ordinary least squares (OLS) and two-stage least squares (2SLS) estimations reveal a negative relationship between housing prices and firms' robot adoption. The effect is economically substantial: a 10% increase in housing prices over the period 2000–2013 reduces the probability of a firm adopting robots by 1.44 percentage points. The adverse impact is particularly pronounced for firms with high external financing dependence and for non-state-owned enterprises, whereas it is attenuated in firms characterized by low industry capital intensity and skill intensity. Furthermore, firms' investments outside their core business activities are found to crowd out robot adoption. In contexts of weaker corporate governance, which exacerbate managerial short-termism, the negative effect of elevated housing prices is further amplified.

This study investigates how housing prices deter the adoption of robots. First, financial constraints limit adoption, as firms with liquidity shortages cannot cover installation and maintenance costs. Rising housing prices can enhance financing capacity via the collateral effect (Chaney et al., 2012), thus facilitating robot adoption. However, they may simultaneously inhibit adoption through crowding out, as convenient lending opportunities from real estate industry constrain the manufacturing firm's commercial credit and raise its borrowing costs. To disentangle these opposing channels, we use the interaction between housing prices and firms' external finance dependence (Rajan and Zingales, 1998). Empirical results indicate a significantly negative interaction, suggesting that the crowding-out effect outweighs the collateral effect. Another key channel is the speculation effect: high returns from real estate incentivize manufacturing firms to diversify into the sector, diverting resources from robot adoption and undermining long-term development. Robot adoption, central to intelligent production, drives technological upgrading and productivity enhancement (Jung and Lim, 2020). Third, housing prices also affect labor costs: higher housing prices increase workers' living expenses, raising labor costs. Since labor and robots are production substitutes (Fan et al., 2021), rising labor costs encourage labor-intensive firms to adopt more robots. Conversely, in high-skilled-intensive firms, sharply higher labor costs—due to the necessity to attract and retain talent—may force budget-constrained firms to reduce automation investment, lowering robot adoption.

Despite extensive research on the economic consequences of robot adoption and housing booms, critical gaps remain. First, while studies have analyzed the effects of robots on productivity and employment (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Koch et al., 2021), the determinants of robot adoption—especially in emerging economies—are under-explored. Existing works focused on labor costs and policy (Cheng et al., 2019; Fan et al., 2021), overlooking the role of asset price shocks like housing inflation. Second, although literature documents housing booms' adverse effects, such as crowding out innovation (Rong et al., 2016), human capital investment (Charles et al., 2018) and entrepreneurship (Li and Wu, 2014), little is known about the effects on technological upgrading, such as robot adoption. Third, prior evidence on diversification's effect on firm value is mixed: some report a diversification discount (Stowe and Xing, 2006; Hoechle et al., 2012; Liu and Suzuki, 2025), others document a diversification premium (Santalo and Becera, 2008; Kuppuswamy and Villalonga, 2016), while several find no significant effect (Villalonga, 2000; Elsas et al., 2010).

Our study fills these gaps. First, we are the first to identify housing prices as a critical constraint on robot adoption. In addition, unlike most studies that rely on IFR industry-level data from developed economies, we construct firm-level measures, providing empirical evidence from a developing economy. Second, we show high housing prices negatively affect firms' robot adoption through resource constraints and labor costs, offering new evidence on how high housing prices constrain long-term industrial upgrading. Third, our study highlights the diversification into the real estate crowds out the robot adoption. In addition, our paper relates to prior research, with the most relevant being Rong et al. (2016), who show that housing price appreciation crowds out manufacturing firms' innovation activity by diverting resources to real estate. This study is among the first to examine how housing prices and non-core speculation affect robot adoption in China's overheated housing market.

The remainder of the paper is organized as follows. Section 2 reviews Chinese housing reforms and the robotics industry. Section 3 develops the theoretical development and Hypotheses. Section 4 describes the data and variable construction. Section 5 presents our empirical specification. Section 6 displays the baseline results and addresses endogeneity concern. Section 7 discusses the robustness of our main results, and Section 8 examines heterogeneity and underlying mechanisms. The final section concludes.

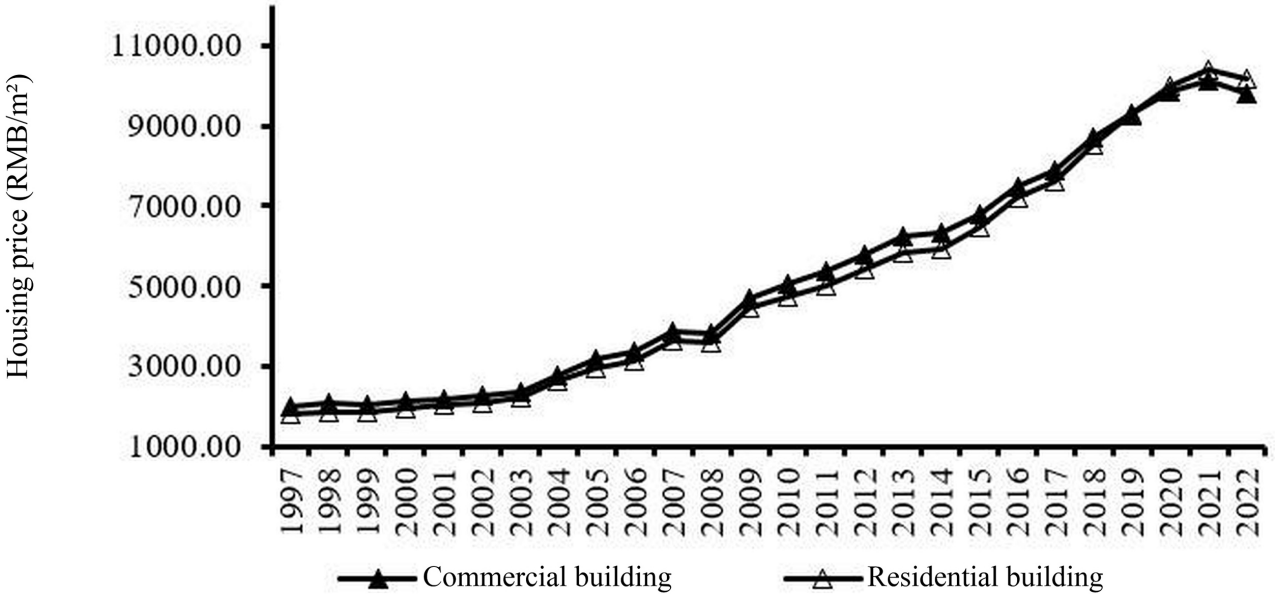


Fig. 1. China's housing prices over time. Notes: The figure is provided for background illustration and covers 1997–2022, which extends beyond the core empirical sample period of 2000–2013. National average housing prices are directly obtained from the China Statistical Yearbook of Regional Economy.

2. Background

The 1997 Asian financial crisis prompted China to seek new sources of economic growth. To stimulate domestic demand, the State Council issued the "Resolution on Continuing Urban Housing System Reform and Accelerating Housing Development", formally ending the welfare housing system and ushering in the era of housing commercialization. The real estate sector subsequently expanded, supported by the People's Bank of China, which lowered mortgage rates five times between 1998 and 2002 and introduced measures such as broader real estate loan eligibility and developer pre-installments to promote housing market development further. In 2003, the State Council issued the "Notice on Promoting the Sustainable and Healthy Development of the Real Estate Market" (No. 18 [2003])[1] ([1]Information about the Notice from the Chinese Government Website at: https://www.gov.cn/zhengce/zhengceku/2008-03/28/content_4797.htm.), which first designated real estate as a "pillar industry of the national economy". Following comprehensive housing market reforms, real estate prices surged, with housing prices rising 316% from 2003 to 2022, as shown in Fig. 1.

Following Acemoglu and Restrepo (2018), we focus on robots, defined by the IFR as automatically controlled, reprogrammable machines capable of performing multiple tasks. Industrial robots are increasingly vital in modern manufacturing, driving China's transition from a "major manufacturing country" to a "manufacturing powerhouse" and supporting high-quality economic development. Chinese government policy influences the development of China's robotics industry (Cheng et al., 2019). To promote digitization and intelligent manufacturing, the government launched "Made in China 2025", identifying robotics as one of ten key sectors. By 2035, China aims for a globally leading robot industry, with robots playing a vital role in economic development, daily life, and social governance.

3. Theoretical Development and Hypotheses

House-price increases could affect firm's robot adoption through a mix of resources constraints and labor costs. Robots require substantial initial investment, ongoing maintenance, and operators. While some robots are fully automated, others have specialized requirements. A few simple robots may be maintained by a single individual, but this still entails hiring or training personnel. Consequently, firms need sufficient funds to cover the costs associated with expanding robot adoption. Thus, resources constraints can hinder firm's ability to adopt robots. In contrast, rising labor costs alter the relative returns and urgency of automation, potentially enhancing robot adoption intention. The net effect of an increase in housing prices is the net outcome of weighing the resource constraint against the investment incentive brought by labor costs, and behaves differently across firm heterogeneity. In this section, we construct an integrated framework and develop corresponding hypotheses.

3.1 Resource Constraints

First, consider the effect of external finance crowding-out on firm's robots. In developed countries, housing booms increase firms' collateral value—such as land and plants—enhancing access to funds for investment (Lim et

al., 2023; Chaney et al., 2012; Gan, 2007) and innovation (Liu and Suzuki, 2024; Mao, 2021). However, in China's institutional context, the collateral effects that ease external financing elsewhere are absent, and rising housing prices may reduce external finance capacity via a crowding-out effect (Wu et al., 2015). Why the crowding-out effect dominates the collateral effect in China. The reason can be explained by the unique institutional characteristics of China's financial market. Specially, the state-owned banks exhibit a strong policy-driven bias, systematically reallocating credit toward the real estate sector and state-owned enterprises during housing booms. This shift reduces credit availability for manufacturing firms, especially non-state-owned enterprises (Chen et al., 2015; Shi et al., 2016). In addition, the crowding-out effect is further amplified by China's incomplete interest rate liberalization (Song and Xiong, 2018). Under prevailing interest rate controls, banks lack the ability to price risk adequately for loans to private manufacturing firms. Consequently, they are rationally incentivized to reallocate credit toward the seemingly safer and policy-favored real estate sector, which offers attractive returns under regulated rates (Chen et al., 2017; Wu et al., 2015). This systemic distortion means that even when a firm's collateral value increases, it may not obtain additional financing because the institutional friction weakens the traditional collateral channel (Hau and Ouyang, 2019).

Second, consider the internal capital misallocation driven by firm's diversification strategy. High housing prices may tempt managers to divert limited capital toward short-term, speculative real estate investments at the expense of technology upgrading or productivity (Yu et al., 2021). Extensive literature confirms that real estate booms attract corporate resources away from innovation. For instance, Miao and Wang (2014) find that real estate bubbles attract capital to the property sector, thereby reducing innovation. Rong et al. (2016) show that rising real estate values prompted Chinese listed firms to diversify into the real estate industry, which lowered their invention patenting. Similarly, Shi (2018) demonstrates that, although financial constraints may be alleviated through the "collateral enhancement" channel, sustained investment in real estate crowds out research and development (R&D) spending and technology upgrading. Robot adoption also follows a similar pattern. When housing prices rise, firms divert resources into real estate, reducing technological investments such as robot adoption.

3.2 Labor Cost

Rising housing prices increase workers' cost of living, leading firms to raise wages and thereby elevating labor costs. This increase influences robot adoption through two primary mechanisms derived from the task-based model (Acemoglu and Restrepo, 2018; Tang et al., 2021).

First, it strengthens the substitution effect. According to the task-based model, firms decide to adopt robots by comparing the ongoing expense of labor with the fixed cost of automation (Acemoglu and Restrepo, 2020; Autor et al., 2003). When housing-driven living costs push wages higher, the marginal benefit of replacing workers with machines increases, particularly for routine and codifiable production tasks. This makes the investment in robots economically viable, as firms seek to reduce variable labor costs. The positive link between labor costs and automation incentives is widely documented. For example, cross-country studies show that industries facing higher wages adopt robots more intensively (Graetz and Michaels, 2018), and firm-level evidence confirms that automation investment rises in response to labor cost pressures (Koch et al., 2021). This mechanism is also evident in China's manufacturing sector, where rising wages have been a significant driver of industrial robot adoption (Huang et al., 2022; Cheng et al., 2019). Thus, for firms whose production relies heavily on routine tasks, housing-induced labor cost inflation can actively encourage robot adoption as a strategy to restore cost competitiveness.

Second, it may trigger a countervailing budget constraint effect. For high-skill firms, production depends on complex, non-routine tasks that are difficult to automate with existing robotics (Autor et al., 2003; Acemoglu and Restrepo, 2020). Labor costs are inherently high due to the premium on specialized human capital (Börschlein et al., 2024). When housing prices further inflate these wages, firms face a pure cost increase without an automation-based offset, as robots cannot substitute for core high-skill labor. This housing-induced financial squeeze tightens the overall budget. Consequently, they are likely to absorb the shock or cut capital expenditures—including investments in robots. This explains why the negative effect of housing prices on robot adoption is stronger in skill-intensive sectors.

3.3 Hypotheses

A firm's final decision on robot adoption is the combination of resource constraints and investment incentives, and differs across firm heterogeneity. When the resource constraint channel works, rising housing prices disproportionately harm firms reliant on external finance. These firms depend on accessible loans for major investments like advanced robots. When credit is crowded out, they must prioritize operational liquidity over such upgrades, forcing deep cuts to robotics adoption. Thus, the negative effect of housing prices on robot investment is most acute for these firms with high external finance dependence.

Non-state-owned enterprises (NSOEs) generally face greater financing constraints than state-owned enterprises (SOEs) due to credit discrimination in China's financial system (Li et al., 2008; Liu and Suzuki, 2024). They are disproportionately crowded out of bank lending, which flows toward real estate and state-owned firms (Brandt and Li, 2003). Additionally, NSOEs benefit less from rising collateral values due to weaker legal enforcement

and fewer prime real estate holdings (Hau and Ouyang, 2019)[2] ([2]Generally, weaker internal governance mechanisms in NSOE—such as less formalized risk management and board oversight—may exacerbate the adverse effect of constrained external finance, further limiting investment in advanced technologies like robotics. To test whether non-state-owned enterprises are more affected by financial constraints or governance deficiencies, we further explore the different mechanisms in these firms. See more details in Appendix Table 10.). These compounded constraints limit their access to the substantial, long-term capital, leading to a sharper decline in adoption.

Firms with weak corporate governance are more prone to diversify into real estate (Huang and Rong, 2017), resulting in capital misallocation. According to agency theory (Jensen and Meckling, 1976), weak governance exacerbates manager-shareholder conflicts, leading to managerial myopia. In the context of rising housing prices, this problem manifests as a preference for short-term real estate speculation over long-term technological investment like robot adoption. Two key governance mechanisms aggravate this myopia through specific paths. First, weak board monitoring, reflected in a lower proportion of independent directors, impairs oversight of strategic investment (Kim and Lu, 2011). Without sufficient independent scrutiny, management faces less restriction to diverting resources into short-term real estate speculation, thereby crowding out core technological investments like robot adoption (Bebchuk and Fried, 2006). Second, insufficient executive equity incentives fail to align managerial interests with long-term firm value. When managers hold little equity, their personal wealth is closely related to the firm's future performance, increasing their incentive to pursue short-term gains from housing markets at the expense of long-term projects such as robot adoption (Edmans, 2009).

Based on this analysis, we propose the following hypotheses:

H1: Rising housing prices reduce firm's robot adoption by exacerbating resource constraints. The negative effect of rising housing prices is stronger for firms with high external finance dependence, for non-state-owned enterprises, and for firms with weaker corporate governance.

The labor cost channel focuses on how housing-driven increases in labor costs change the marginal benefit and willingness of firms to substitute machines for labor. Its effect is heterogeneous, potentially manifesting as either "cost-driven substitution" or "budget-squeeze suppression". On one hand, for labor-intensive firms with standardized production processes easily automated, rising labor costs directly increase the relative expense of using human labor, thereby strengthening the economic incentive to adopt robots (Acemoglu and Restrepo, 2020). Here, labor cost inflation acts as a catalyst, potentially enhancing investment intention.

On the other hand, for high-skill intensive-firms reliant on a well-educated and creative workforce (Ochoa, 2013), their core advantage lies in human capital. Housing-driven increases in living costs force these firms to pay higher efficiency wages to attract and retain talent (Börschlein et al., 2024), significantly raising overall costs. However, because production in these firms is complex and robots cannot easily substitute for core human skills, the marginal benefit of automation investment is less clear. Under budget constraints, firms may be compelled to cut other capital expenditures, including robot investment, to sustain high labor costs (Autor et al., 2003; Acemoglu and Restrepo, 2020; Tang et al., 2021). Here, rising labor costs primarily exert a "budget squeeze" effect.

Based on this analysis, we propose the following hypotheses:

H2: Rising housing prices affect robot adoption through the labor cost channel. The negative effect of rising housing prices is weaker in labor-intensive firms but is stronger in high-skill intensive firms.

4. Data

4.1 Data Source

The data are drawn from three sources. The Chinese Annual Survey of Industrial Firms (ASIF) provides information on firms' basic characteristics, the China Customs Database (CCD) offers data on robot imports, and the China Statistical Yearbook of Regional Economy (CSYRE) supplies city-level variables, including population, unemployment rate, and per capita Gross Domestic Product (GDP). The ASIF, collected by the Chinese National Bureau of Statistics (NBS), covers all state-owned industrial firms and large non-SOEs with annual sales exceeding five million yuan (approximately US$800,000) from 1998 to 2013. It includes detailed firm-level information such as size, ownership, and capital-labor. Following Feenstra et al. (2013) and Brandt et al. (2012), we apply the Generally Accepted Accounting Principles (GAAP) to delete observations[3] ([3]Observations are excluded from the analysis if they satisfy the GAAP rules: liquid assets more than total assets/total fixed assets more than total assets more/net fixed assets greater than total assets/missing firm identification numbers/an invalid established time exists.). This cleaning process helps maintain a reliable dataset for subsequent empirical examination.

The CCD records firms' import and export transactions, with commodity Harmonized System codes available at the eight-digit level (HS8 codes). These codes provide detailed descriptions, allowing identification of industrial robot imports. Following Fan et al. (2015) and Lu and Yu (2015), we use two methods to merge ASIF with CCD for 2000–2013. First, we match the two data sets by using each firm's Chinese name and year. Second, to further augment the matched sample, we link firms using their postal code and the last seven digits of their phone number. Further-

more, we have added a data construction flowchart to visually summarize the entire process in Appendix Fig. 4.

Additionally, given the substantial differences between trading intermediaries and manufacturing firms in terms of import/export motives and production behavior, trading intermediary samples were excluded. After merging ASIF with CCD, we obtain a panel from 2000 to 2013. To analyze the impact of housing prices on robot adoption, we supplemented the panel with city-level variables from the CSYRE. The final dataset contains information on robot imports, firm characteristics, and housing prices.

4.2 Robot Adoption Measure

The International Federation of Robotics (IFR) provides data on robot adoption; however, it is only available at the national and sectoral levels. Empirical research, by contrast, requires measures of robot adoption at a disaggregated firm level. Some firm-level surveys, such as those used by Cheng et al. (2019), provide such data, but they rely partly on respondents' subjective judgment of what constitutes a robot. In contrast, our measure is derived from the customs database, an administrative source, allowing robot adoption to be verified precisely by customs officials.

Specifically, following Fan et al. (2021), we construct an industrial robot measure using HS8 codes, including: 85153120 (arc welding robots), 84795010 (multifunctional industrial robots), 84795090 (other unlisted industrial robots), 85152120 (other resistance welding robots, automotive production line resistance welding robots), 85158010 (other laser welding robots, automotive production line laser welding robots), 84248920 (spraying robots), 84289040 (handling robots), and 84864031 (automatic handling robots for IC factories). To capture firm-level robot adoption, we calculate the firm's imported robots in a given year based on transaction records. Globally, IFR aggregates robot shipments by country for each year. Using both the customs and IFR databases, Fig. 2 provides a descriptive illustration of the trends in robot adoption from 2001 to 2012, while the main empirical analysis is based on the full sample period of 2000–2013. Two stylized facts emerge. First, IFR-reported robot sales are lower than those in the customs data, likely due to IFR's more restrictive definition of industrial robots or, potentially, strategic underreporting by national robot suppliers. Second, the customs data exhibit similar trends to IFR data, validating our use of customs-based measures of robot adoption from 2000 to 2013.

4.3 Stylized Facts

Table 1 presents the summary statistics of the main variables, indicating that, on average, only 6% of firms have adopted robots. Variable definitions and data sources are provided in Appendix Table 9. Robot usage in China remains generally modest, consistent with Fan et al. (2021). Table 2 reports the average probability and value of robot adoption across firms by industry skill intensity, capital intensity, SOE status, and external finance dependence.

Table 1. Summary statistics.

Variables	No.obs.	Mean	Std.dev	Min	Max
Dependent variables					
Robot value	414,807	0.687	2.775	0.000	18.970
Adoption probability	414,807	0.060	0.237	0.000	1.000
Independent variable					
Housing prices	414,807	8.511	0.627	6.084	9.969
Firm controls					
Age	364,641	9.043	7.721	0.000	161.000
Capital intensity	351,982	4.036	1.478	–6.116	13.400
Size	414,807	11.010	1.527	0.000	19.450
Export status	414,807	0.376	0.484	0.000	1.000
Industry controls					
FIE no	414,714	6.660	1.376	0.000	9.265
SOE share	414,807	0.022	0.030	0.000	0.667
City controls					
City population	414,744	6.265	0.701	2.819	9.315
City investment	414,532	–0.897	0.365	–2.439	1.136
City GDP per capita	404,879	10.880	0.649	4.595	13.060
Unemployment rate	414,616	0.046	0.027	0.000	0.560

Notes: FIE, Foreign-Invested Enterprise; SOE, State-Owned Enterprise; GDP, Gross Domestic Product. Adoption probability is a binary indicator equal to 1 if a firm has adopted robots and 0 otherwise, and is therefore unitless. Robot value is the inverse hyperbolic sine (IHS) transformation of the firm's robot import value (originally measured in RMB) and is therefore reported on the transformed scale.

High-capital-intensity firms adopt robots more frequently (7.5% vs. 2.7%) and at higher values (0.866 vs. 0.291) than low-capital-intensity firms. Similarly, high-skill-intensive firms show the highest adoption probability (10.3%) and robot value (1.199), while low-skill-intensive firms lag behind. Ownership type has a modest effect, with non-SOEs showing slightly higher adoption rates than SOEs. Overall, these statistics suggest that capital intensity and skill intensity are positively associated with robot adoption.

This regional variation is graphically illustrated in Fig. 3, which shows the average urban housing prices from 2000 to 2013. The darker the color, the higher the housing prices (HP) the city has. The contrast in colors on the map indicates that our data exhibit substantial cross-sectional variations across regions, which can verify our causal identification. Among cities with available data, higher housing prices are primarily concentrated in the eastern coastal regions, particularly in Jiangsu, Zhejiang, and Shanghai.

5. Empirical Strategy

To investigate the relationship between housing prices and robot adoption, we first specify a baseline model and estimate it without instrumental variables (non-IV).

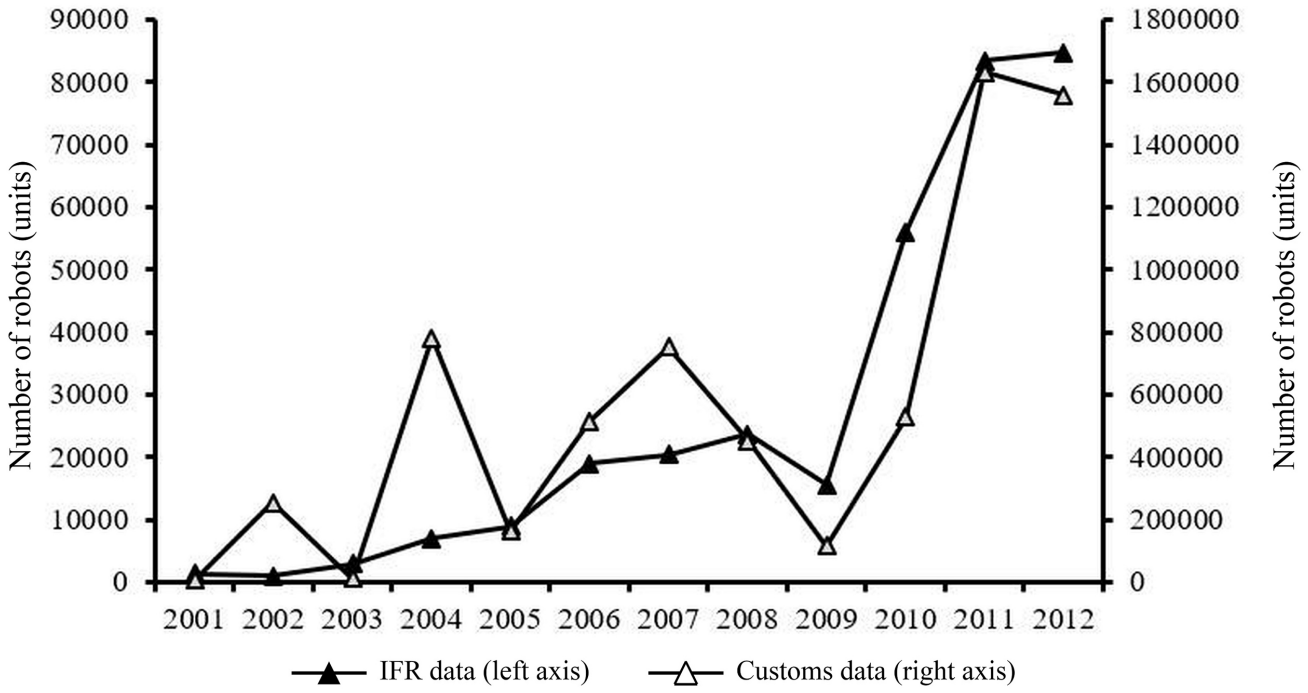


Fig. 2. Adoption of robots in China over time. Notes: The data come from the International Federation of Robotics (IFR) and the Chinese Customs Database (CCD).

$$Y_{ft} = \beta_0 + \beta_1 \ln(hp_{ct}) + \theta Z_{ft} + \gamma Z_{it} + \delta Z_{ct} + \mu_f + \mu_t + \varepsilon_{ft} \quad (1)$$

Here, the subscripts *f*, *c*, and *t* denote the firm, city, and year. The dependent variable Y_{ft} refers to the robot adoption by firm *f* in year *t* and takes two forms. The first is a binary indicator equal to 1 if the firm uses robots in production and 0 otherwise. The second, $Robot_{it}$ represents the value of robots employed by the firm. $\ln(hp_{ct})$ denotes the commercial housing price in city *c* in year *t* lagged by one year, to account for firms' delayed response to housing price fluctuations, thereby mitigating potential heterogeneity concerns. We expect the estimated β_1 be negative and statistically significant, reflecting the adverse effect of housing prices on robot adoption. Z_{ft} represents firm characteristics, while Z_{it} and Z_{ct} capture industry and city controls, respectively. μ_f denotes the firm fixed effect, controlling for all time-invariant characteristics across firms, and μ_t represents the year fixed effect, controlling for all yearly shocks common to all firms. ε_{ft} is the error term. The standard errors are clustered at the firm level.

This empirical model uses two measures of robot adoption as dependent variables. The first measure is adoption probability, equal to 1 if the firm has adopted robots and 0 otherwise. The second is the robot import value, transformed as: $Y_{ft} = \ln[y_{ft} + \left(y_{ft}^2 + 1\right)^{\frac{1}{2}}]$, where y_{ft} is the robot import value of firm *f* in year *t*. This transformation, used by Burbidge et al. (1988) and Pence (2006), preserves zero observations and provides flexibility. Our results remain robust when using *ln*(*robot*+*1*) as an alternative. Unlike some existing literature that focuses on the quantity of robot imports, the import value is preferred in our study as it accounts for differences in robot size and better reflects the automation level of machinery and equipment.

A set of firm characteristics *X* are included, such as firm size, age, capital-labor ratio, and export status[4] ([4]Firm size captures internal resources, economies of scale, and access to finance (Beck et al., 2005), while the capital-labor ratio directly measures automation intensity and production technology. Both factors independently determine a firm's capacity and incentive for technology investment. Firm age captures non-linear lifecycle dynamics, such as learning effects, organizational inertia, and survival bias (Coad et al., 2018). Export status captures international competition and higher quality standards, which compel technology upgrading (Bernard et al., 2007; Melitz, 2003).). To control for SOE reforms and the relaxation of foreign direct investment (FDI) entry regulations, we add two additional industry-level variables: SOE share (the proportion of SOEs among domestic firms) and FIE no (the logarithm of the number of foreign-invested firms)[5] ([5]SOE Share captures structural differences in incentives, innovation capacity, and the legacy of state ownership across industries, which are critical in China's transitional economy (Jefferson et al., 2000). Number of FIEs measures the degree of foreign competition, knowledge spillovers, and FDI policy liberalization, all of which influence domestic firms' tech-

Table 2. Summary statistics by subsamples.

Variables	No.obs.	Mean	Std.dev	Min	Max
By external finance dependence					
Low ExtFinDep					
Robot value	168,991	0.491	2.371	0.000	18.710
Adoption probability	168,991	0.043	0.203	0.000	1.000
High ExtFinDep subsample					
Robot value	245,816	0.821	3.014	0.000	18.970
Adoption probability	245,816	0.072	0.258	0.000	1.000
By ownership status					
SOEs					
Robot value	7587	0.697	2.900	0.000	18.850
Adoption probability	7587	0.057	0.232	0.000	1.000
Non-SOEs					
Robot value	407,220	0.686	2.773	0.000	18.970
Adoption probability	407,220	0.060	0.238	0.000	1.000
By capital intensity					
Low capital intensity					
Robot value	129,464	0.291	1.793	0.000	16.330
Adoption probability	129,464	0.027	0.161	0.000	1.000
High capital intensity					
Robot value	285,343	0.866	3.104	0.000	18.970
Adoption probability	285,343	0.075	0.263	0.000	1.000
By skill intensity					
Low skill intensity					
Robot value	246,289	0.336	1.940	0.000	18.770
Adoption probability	246,289	0.031	0.172	0.000	1.000
High skill intensity					
Robot value	168,518	1.199	3.607	0.000	18.970
Adoption probability	168,518	0.103	0.304	0.000	1.000

Note: ExtFinDep, External Finance Dependence.

nology adoption decisions (Javorcik, 2004).). Following Fan et al. (2021), X also incorporates city-level controls, including population, investment, GDP per capita, and unemployment rate[6] ([6]Population and GDP per capita represent local market size, economic development, and wage levels. Higher wages (proxied by GDP per capita) are a primary driver of automation via the induced innovation (Acemoglu and Restrepo, 2018). Investment and unemployment rate account for local investment climate and business cycles, which affect overall investment demand and factor costs (Glaeser et al., 1995).). Regarding the multicollinearity concern, we have conducted Variance Inflation Factor (VIF) tests, and the results indicate no severe multicollinearity issues, with all VIF values well below 10 and a mean VIF of 1.68. The full VIF table will be included in Appendix Table 11.

Even with a comprehensive set of control variables, housing prices may remain endogenous due to two primary concerns (Hill et al., 2021). First, reverse causality could arise if firms' technology imports enhance local productivity and wages, thereby stimulating housing demand and elevating prices. Second, omitted variable bias may occur if unobserved, time-varying city-level factors, such as shifts in industrial policy or local technological dynamism, simultaneously influence both housing prices and firms' automation investments. To address this endogeneity issue, we adopt a 2SLS approach to identify the causal effect of housing prices on robot adoption. In the first stage, housing prices are regressed on all exogenous variables:

$$\ln(hp_{ct}) = \beta_0 + \beta_2 IV_{ct} + \theta Z_{ft} + \gamma Z_{it} + \delta Z_{ct} + \mu_f + \mu_t + \varepsilon_{ft} \quad (2)$$

Here, IV_{ct} serves as the instrumental variable for housing price, while other variables are as defined in Eqn. 1. Following Chaney et al. (2012) and Wrenn et al. (2019), we construct the instrumental variable as the interaction between an indicator for whether a city's average slope exceeds the national average and long-term interest rates. The average city slope of each city is derived from the Shuttle Radar Topography Mission (SRTM) elevation data in ArcGIS 10.3, produced by the Chinese Academy of Sciences, Beijing. Long-term lending rates are weighted averages re-

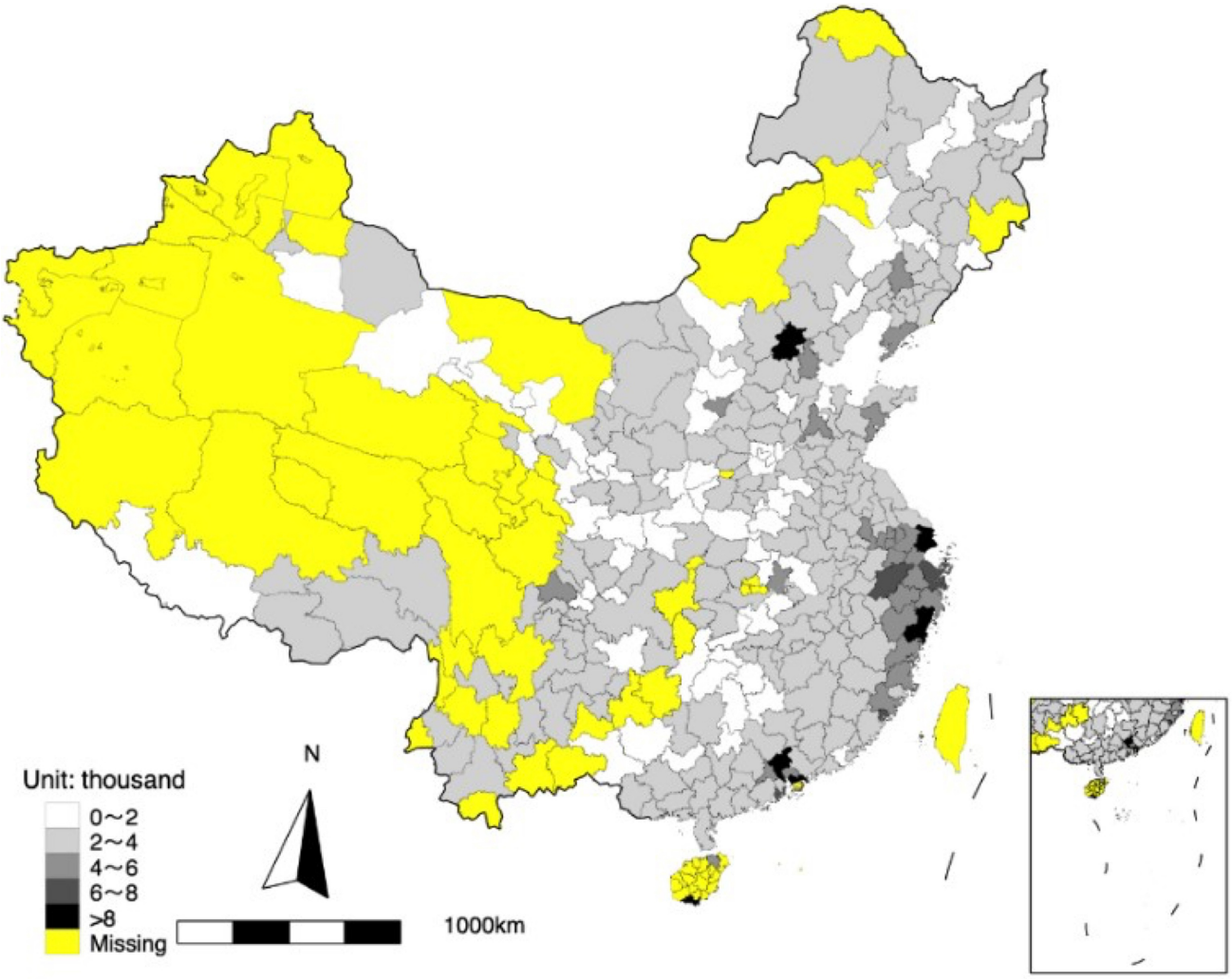


Fig. 3. Regional average housing price differences. Notes: This figure shows the average housing prices in 295 Chinese cities from 2000 to 2013.

flecting the share of days in a year when a specific rate is active, accounting for multiple annual adjustments by the People's Bank of China.

We estimate Eqn. 2 using OLS to obtain predicted values $\hat{\ln}(hp_{ct})$.

$$\ln(hp_{ct}) = \hat{\ln}(hp_{ct}) + \xi_{ft} \tag{3}$$

Substituting Eqn. 3 into Eqn. 1 yields the second-stage regression:

$$\begin{aligned} Y_{ft} = \beta_0 + \beta_1 \hat{\ln}(hp_{ct}) + \theta Z_{ft} + \gamma Z_{it} \\ +\delta Z_{ct} + \mu_f + \mu_t + (\beta_1 \xi_{ft} + \varepsilon_{ft}) \end{aligned} \tag{4}$$

In Eqn. 4, $\hat{\ln}(hp_{ct})$ is uncorrelated with the composite error term $(\beta_1 \xi_{ft} + \varepsilon_{ft})$, ensuring a consistent estimate of β_1.

6. Empirical Results

6.1 Basic Results

The estimation results based on Eqn. 1 are displayed in Table 3. To save space, we only present coefficients for the key variable of housing price. In Panel A, the dependent variable is whether a firm has adopted robots. Column (1) includes only year and firm fixed effects. Column (2) adds time-varying firm-level characteristics (age, size, capital intensity, export status, and ownership type) as well as industry-level characteristics (SOE share and FIE). Column (3), the preferred specification, further incorporates city-level controls (see notes on Table 3). Across all three columns, the estimated coefficients on ln *HP* are negative and statistically significant. In particular, Column (3) reports a coefficient of –0.014, significant at the 1% level, implying that a 10% increase in housing prices reduces the probability of robot adoption by 0.14 percentage points.

In Panel B, the dependent variable is robot value, and the same sequence of controls is introduced as in Panel A.

Table 3. Effects of housing price on robot adoption.

	(1)	(2)	(3)
Panel A: Adoption probability			
ln *HP*	–0.006*	–0.014***	–0.014***
	(0.004)	(0.004)	(0.004)
R-squared	0.470	0.484	0.484
Observations	380,175	319,291	318,845
Panel B: Robot value			
ln *HP*	–0.090**	–0.178***	–0.175***
	(0.044)	(0.048)	(0.049)
R-squared	0.502	0.515	0.515
Observations	380,175	319,291	318,845
Robot-adopting firms			
Panel C: Robot value			
ln *HP*	–0.181	–0.079	–0.081
	(0.167)	(0.181)	(0.182)
R-squared	0.624	0.639	0.639
Observations	18,336	15,105	15,078
Firm controls	NO	YES	YES
Industry controls	NO	YES	YES
City controls	NO	NO	YES
Firm FEs	YES	YES	YES
Year FEs	YES	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and unemployment rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. FE, fixed effects. Panels A and B use the full sample, with zero robot imports retained in Panel B through the ln(1 + robot value) transformation. Panel C is restricted to robot-adopting firms only and therefore has a smaller sample. The smaller numbers of observations reported in subsequent Table 4 and Appendix Table 14 are due to missing data for variables required in the additional specifications. Table 4 excludes observations with missing information for the instrumental variable, while Appendix Table 14 further excludes observations with missing values for total passenger volume and secondary industry share.

All estimated coefficients of ln *HP* are negative and statistically significant. The preferred specification in Column (3) yields a coefficient of –0.175, significant at the 1% level, indicating that a 10% increase in housing prices lowers robot import value by 1.75%.

Panel A thus captures the robot adoption on the extensive margin (whether firms adopt robots), while Panel B reflects both extensive and intensive margins (where firms that already adopted robots choose to increase import value) by analyzing the overall effects on robot value for all firms. The large number of zeros in robot value indicates that the robot adoption patterns are driven by the first-time robot adopters, suggesting the extensive margin dominates the intensive margin. To isolate the intensive margin, Panel C restricts the sample to firms that have already adopted robots. In this case, the estimated coefficients of ln *HP* are negative but not statistically significant, suggesting no robust effect of housing prices on the intensity of robot adoption. This may be due to offsetting mechanisms, such as the crowding-out effect, speculative behavior, and rising labor costs. Overall, Table 3 shows that higher housing prices significantly reduce both the likelihood of robot adoption and the value of robot imports, but exert no significant influence on the intensive margin.

6.2 Endogeneity Concerns

In Table 4, we re-estimate the regression using a 2SLS approach. The results remain robust, with the estimated coefficients retaining the same signs and significance levels as those reported in Table 3. The first-stage results show that the Kleibergen-Paap rk Wald F and Cragg-Donald Wald F statistics in Panels A and B are well above the critical value of 10, indicating no concerns regarding weak instruments[7] ([7]We supplement the exclusivity test of the instrumental variable, see more details in Appendix Table 12. After directly controlling infrastructure levels (total passenger volume) and industrial layout (secondary industry share) that by which instrumental variable may affect firms' robot adoption, our core result remains robust: the coefficient on housing price is –1.677 ($p < 0.01$).). Further, we test endogeneity using a Durbin-Wu-Hausman (DWH) test after implementing a 2SLS approach. The DWH test rejects the null of exogeneity ($p = 0.034$) in Panel A and B, confirming the presence of endogenous bias. Moreover, all instruments are statistically significant and negatively signed, consistent with prior literature using housing supply elasticities and long-term interest rates as instruments for housing prices. However, it is weak for the intensive margin subsample in Panel C. Fortunately, this does not undermine our conclusions. The key result in Panel C is itself a statistically insignificant effect of housing prices. The main risk of a weak instrument—exaggerating a significant finding—is therefore not present. The Panel C sample consists only of firms that have already adopted robots, a group likely to be less financially constrained and thus less sensitive to the credit-crowding-out mechanism. Consequently, it is theoretically plausible that our instrument (constructed based on macro-credit channels) has weaker predictive power for housing price variation within this particular, less-sensitive subsample. This does not invalidate the instrument but reflects sample heterogeneity.

Panel A reports results for robot adoption probability. The estimated coefficient on ln *HP* remains negative and statistically significant across all specifications, with larger magnitudes than that in Panel A of Table 3. For instance, Column (3) indicates that a 10% increase in housing prices over the 2000–2013 period reduces a firm's probability of adopting robots by 1.44 percentage points. In Panel B, which uses robot value as the dependent variable,

Table 4. IV results: Effects of housing price on robot adoption.

	(1)	(2)	(3)
The second stage			
Panel A: Adoption probability			
ln *HP*	–0.162	–0.152*	–0.144*
	(0.103)	(0.082)	(0.078)
Observations	379,972	319,137	318,691
Panel B: Robot value			
ln *HP*	–2.280*	–2.173**	–2.036**
	(1.173)	(0.939)	(0.882)
Observations	379,972	319,137	318,691
Panel C: Robot value (Robot-adopting-firms)			
ln *HP*	1.907	0.703	0.729
	(3.822)	(3.697)	(3.790)
Observations	18,328	15,098	15,071
The first stage			
$\text{Slope}_C^D \times$ Rate	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Kleibergen-Paap rk Wald F statistic			
Panel A	215.850	406.992	466.116
Panel B	215.850	406.992	466.116
Panel C	4.318	19.040	18.711
Durbin-Wu-Hausman (DWH) test *p*-value			
Panel A	0.065	0.032	0.034
Panel B	0.065	0.032	0.034
Panel C	0.558	0.802	0.801
Firm controls	NO	YES	YES
Industry controls	NO	YES	YES
City controls	NO	NO	YES
Firm FEs	YES	YES	YES
Year FEs	YES	YES	YES

Notes: The control variables are the same as those reported in Table 3. IV, Instrumental Variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The Kleibergen–Paap rk Wald F statistic is reported to assess instrument strength under heteroskedasticity-robust and cluster-robust inference As a rule of thumb, values above 10 indicate that weak-instrument concerns are limited.

the coefficient of ln *HP* remains negative and statistically significant at the 5% level, suggesting that higher housing prices reduce robot import value. Panel C restricts the sample to robot-adopting firms to examine the intensive margin of robot adoption. Consistent with Panel C of Table 3, we do not find a significant effect on the intensive margin.

7. Robustness Checks

In this subsection, we conduct several sensitivity analyses to further assess the robustness of our findings[8] ([8] We further conduct a series of sensitivity check. First, we re-estimated our model using residential housing prices excluding affordable housing and the growth rate as alternative measures. Second, we addressed extreme values through the following approaches: Winsorizing both housing price and robot adoption variables at the 1% level bilaterally; excluding cities with compound annual housing price growth rates exceeding 10%; excluding firms with the highest 1% of robot import volumes. Third, we check the interference of policy shocks in 2003 and 2008. Fourth, we have also tested the robustness of our findings using the annual growth rate of housing prices. Finally, concerning the estimates may be driven by the omission of these domestically produced robots. We drop manufacturing electrical, electronic, rubber, and plastic products industries that are main customers of Chinese robot suppliers. In all these subsamples, our core conclusion remains unchanged (see Appendix Table 12 for details). Considering the interference of policy shocks (such as the impact of exogenous shocks such as the designation of real estate as a pillar industry in 2003 and the 2008 financial crisis on the conclusions), we test the interference of policy shocks (see Appendix Table 13 for details).), with results reported in Table 5. First, we examine whether the results are sensitive to alternative estimation methods. While the main model uses OLS to estimate the effect of housing prices on robot adoption, we now employ a fixed-effects Poisson model to account for the large number of zeros in the robot import data. In Panel A, column (1), the dependent variable is robot adoption probability, while in Panel B, column (1), it is robot value. In both cases, the coefficient on housing prices remains negative and statistically significant, indicating an adverse effect of housing prices on robot adoption. Next, we test the robustness of our results to alternative measures of robot adoption. Following Acemoglu and Restrepo (2022), we use HS8 codes 84795010 and 84795090 to calculate robot imports. Column (2) of Table 5 reports results based on these codes. The estimated effects of housing prices remain negative and statistically significant.

Finally, we address potential concerns regarding the sample period. In the late 1990s, China began transitioning from a welfare housing system toward the privatization and commercialization of urban housing. Pilot experiments in several cities allowed the full or partial property rights of public housing are sold to state-sector employees in 1994. The 1998 State Council "Resolution on Continuing Urban Housing System Reform and Accelerating Housing Development" further required work units to stop providing public housing, prompting individuals to purchase commercial housing. From 1998 to 2002, housing prices changed moderately, but prices rose sharply from 2003 onward. To test robustness to an alternative period of rapid housing price growth, we restrict the sample to 2003–2013. Results in column (3) of Table 5 show that the coefficient on housing prices remains significantly negative, indicating that the findings are robust to changes in the sample period.

Table 5. The robustness checks.

	(1) Poisson	(2) HS8 code	(3) Year >2003
Panel A: Adoption probability			
ln *HP*	–0.225***	–0.014***	–0.013***
	(0.067)	(0.004)	(0.004)
R-squared		0.484	0.489
Panel B: Robot value			
ln *HP*	–0.467*	–0.006*	–0.169***
	(0.263)	(0.004)	(0.050)
R-squared		0.472	0.520
Firm controls	YES	YES	YES
Industry controls	YES	YES	YES
City controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	58,952	318,845	308,867

Notes: Robust standard errors in parentheses are clustered at the firm. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and FIE no. City-level controls include investment, population, GDP per capita, and unemployment rate. *** $p < 0.01$, * $p < 0.1$. HS8 code, Harmonized System code available at the eight-digit level.

8. Heterogeneity and Mechanism

In this section, we examine the heterogeneous effects of housing prices on robot adoption. Following the hypotheses outlined in Section 2.3, we investigate how housing prices influence robot adoption across several dimensions: external finance dependence, SOE status, industry capital intensity, industry skill intensity, housing market speculation, and corporate governance.

8.1 Heterogeneous Effects by External Finance Dependence

Previous studies have used external finance dependence to examine how credit constraints affect firms' exports or imports. For example, Manova (2008) shows that financial frictions shape cross-country trade patterns at the sector level. Iacovone et al. (2019) find that industries with greater reliance on external finance experience smaller export growth during banking crises. Behrens et al. (2013) show that firms with above-average reliance on external finance reduce imports more during recessions. The underlying mechanism is that financial constraints prevent firms from covering fixed costs associated with exporting or importing. Recalling the crowding-out channel discussed in Section 2.3.1, when housing prices rise rapidly, banks allocate more credit to land-holding firms, making it harder for non-land-holding firms to access financing. If this channel is correct, firms with higher external finance dependence should experience a stronger decline in robot adoption during housing price booms. Further, we make mediation tests for more direct evidence. We use firms' interest burden, measured as interest expenses divided by total assets, as a proxy for financing pressure. We employ the stepwise regression procedure by Baron and Kenny (1986) to test the indirect effects. The results are presented in Appendix Table 15, showing that housing prices are positively and significantly associated with firms' interest burden. When including interest burden in the baseline regression, the direct effect of housing prices on robot adoption decreased, while the mediators remain significant. These mediation findings directly validate external finance channel.

We divide firms into two sub-samples based on whether their industry's external finance dependence exceeds the 50th percentile of the full sample. Firms above the 50th percentile form the high external finance dependence group (high *ExtFinDep*), while those below form the low *ExtFinDep* group. External finance dependence is measured following Rajan and Zingales (1998) as the share of capital expenditures that cannot pay with internal funds. The high *ExtFinDep* group faces more severe credit constraints.

Columns (1) and (2) of Table 6 report regressions for the low and high *ExtFinDep* groups, respectively. While ln *HP* is negative in both sub-samples, it is statistically significant only in the high *ExtFinDep* group. Column (3) presents results for the full sample, showing that ln *HP* and that on the interaction term with $ExtFinDep^{D}_{high}$ (a dummy that takes the value of 1 if a firm belongs to the high external finance dependence subsample) are both significantly negative. Overall, the evidence indicates that firms with high external finance dependence experience a stronger decline in robot adoption during housing price booms.

8.2 Heterogeneous Effects by Ownership

SOEs in China maintain close ties with the government and benefit from preferential policies such as financial support and subsidized credit (Li et al., 2008; Liu and Suzuki, 2024). Moreover, their extensive holdings of plants, equipment, and other fixed assets provide strong financing capacity, allowing SOEs to face lower credit constraints when housing prices rise rapidly (Allen et al., 2005; Cull and Xu, 2005). As a result, SOEs can more easily overcome the fixed costs of installing robots. In contrast, non-SOEs are more financially constrained, suggesting that the negative effects of rising housing prices on robot adoption are likely more pronounced for them.

To test this prediction, we divide firms into SOEs and non-SOEs. Columns (4)–(5) of Table 6 report regressions for the two subsamples. The estimated coefficient on housing prices is significantly negative only for non-SOEs. In column (6), using the full sample and including an interaction term between housing prices and the SOE dummy, the coefficient on housing prices remains significantly negative. Although the coefficient for the interaction term is

Table 6. Heterogeneous effect by external finance dependence and ownership.

	(1) Low ExtFinDep	(2) High ExtFinDep	(3) Full sample	(4) SOEs	(5) Non-SOEs	(6) Full sample
Panel A: Adoption probability						
ln *HP*	–0.005	–0.015**	–0.002	0.045	–0.015***	–0.014***
	(0.006)	(0.006)	(0.004)	(0.041)	(0.004)	(0.004)
$ExtFinDep^{D}_{high}$			0.162***			
			(0.020)			
$ExtFinDep^{D}_{high} \times lnHP$			–0.019***			
			(0.002)			
$SOEs^{D}$						–0.083
						(0.051)
$SOEs^{D} \times lnHP$						0.010
						(0.006)
R-squared	0.491	0.496	0.484	0.579	0.485	0.484
Panel B: Robot value						
ln *HP*	–0.071	–0.196***	–0.050	0.368	–0.195***	–0.175***
	(0.065)	(0.071)	(0.050)	(0.477)	(0.049)	(0.049)
$ExtFinDep^{D}_{high}$			1.778***			
			(0.229)			
$ExtFinDep^{D}_{high} \times lnHP$			–0.205***			
			(0.027)			
$SOEs^{D}$						–0.860
						(0.643)
$SOEs^{D} \times lnHP$						0.097
						(0.077)
R-squared	0.519	0.528	0.515	0.606	0.515	0.515
Firm controls	YES	YES	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES	YES	YES
City controls	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES
Observations	125,950	181,512	318,845	4465	312,743	318,845

Notes: Robust standard errors in parentheses are clustered at the firm. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. *** $p < 0.01$, ** $p < 0.05$.

not significant, its sign aligns with our research hypothesis. Overall, these results indicate that non-SOEs are more sensitive to housing price increases in their robot adoption. Non-SOEs are more negatively affected by rising housing prices in robot adoption due to weaker governance and limited financing, which makes them more likely to delay or forgo investments. In contrast, the stronger governance and financial support for non-SOEs help sustain their long-term technology investment (Fan et al., 2007; Tian and Estrin, 2008).

8.3 Heterogeneous Effects by the Industry Capital Intensity

Industries differ in characteristics such as capital intensity, which can influence how housing prices affect robot adoption. As Cheng et al. (2019) show, capital intensity varies substantially across industries and is a key determinant of robot adoption. We hypothesize that the adverse effect of rising housing prices is stronger in high capital intensity industries. To test this, we divide industries into two subsamples based on Chinese Industry Classification (CIC) four-digit capital intensity (the simple average of the ratios in those years): high capital intensity industries exceed the 75th percentile, and low capital intensity industries fall below it. Columns (1)–(2) of Table 7 show that the effect of housing prices is significantly negative only for high capital intensity industries. In column (3), introducing the interaction term between ln *HP* and $\text{Capintensity}^{\text{Dummy}}_{high}$ (a dummy that takes the value of 1 if a firm belongs to high capital intensity industries), we find that the coefficient is also significantly negative. Overall, the results indicate that housing

prices reduce robot adoption in high capital intensity industries but have no effect in low capital intensity industries. This pattern aligns with the substitution between labor and robots (Fan et al., 2021): in low capital intensity industries, the incentive to replace costly labor with robots partially offsets the negative impact of rising housing prices.

8.4 Heterogeneous Effects by the Industry Skill Intensity

As documented in Section 2.3.2, rising housing prices increase labor costs by raising employees' wage demands and firm's compensation expenses, disproportionately affecting high-skilled-intensive firms. Consequently, financially constrained firms reduce investment in automation technologies such as robots in faced of increased labor costs caused by high housing prices. We examine the heterogeneous effects by industry skill intensity in Table 7. Following Fan et al. (2021), we define 7 industries as high skill intensity industries[9] ([9]The industry description corresponding to the 2-digit industry codes is as follows: 40, communication equipment, computers, and other electronic equipment; 41, instruments, meters, cultural, and clerical machinery; 37, transportation equipment; 36, special purpose equipment; 30, plastic products; 29, rubber products; 39, electric machinery and equipment.). Regarding the potential dynamic nature of industry skill intensity, we conduct robustness using new measure. The data on skill intensity are calculated from the 1995, 2004 Firm Census in China, and 1980 Firm Census in US by Che and Zhang (2018). As Appendix Table 16 shows, our results are robust to the alternative measure of industry-level skill intensity.

Regression results, reported in columns (4)–(5) of Table 7, show that the coefficient on ln *HP* is significantly negative in both subsamples, but its magnitude is larger for the high skill-intensity group. This indicates that robot adoption in high skill-intensity firms declines more sharply than that in low skill-intensity firms when housing prices rise rapidly. In the full sample regression (column 6), the interaction term between ln *HP* and $\text{Skillintensity}_{high}^{\text{Dummy}}$ (a dummy that takes the value of 1 if a firm belongs to high skill-intensity industries) is also significantly negative. Overall, these results suggest that robot adoption in high skill-intensity industries is particularly sensitive to rising housing prices.

One plausible explanation is that high skill-intensity industries face greater pressures to increase wages and benefits to attract and retain talent during periods of rapid housing price growth (Börschlein et al., 2024), amplifying the labor cost of investing in automation. This mechanism aligns with prior studies on skill intensity, labor costs, and technology adoption (Che and Zhang, 2018). Stronger governance such as better compensation management and strategic resource allocation can help firms mitigate labor cost pressures and maintain long-term technology investment.

8.5 Housing Market Speculation and Corporate Governance Level

As the speculation channel suggests, rising housing prices lead firms to diversify into real estate, reducing robot adoption. For instance, Rong et al. (2016) show that real estate diversification among manufacturing firms leads to a decline in their invention patents, while Shi et al. (2016) similarly report reductions in R&D and patenting amid heated housing markets due to managerial myopia. In firms with weak corporate governance, managers prioritize short-term gains and speculative activities over long-term firm development (Yu et al., 2021). Wang and Wu (2007) provide empirical evidence that stronger corporate governance helps reduce myopic R&D investment decisions, and Mavruk and Carlsson (2015) further demonstrate that managerial myopia significantly diminishes firms' capital expenditures and R&D, and that institutional investors and analyst coverage can mitigate this effect.

To test this, we conduct the following empirical analysis. The ASIF survey provides rich firm-level information but lacks data on real estate investment and governance, preventing a direct test of their effects on robot adoption. We therefore incorporate the China Stock Market and Accounting Research (CSMAR) database, which provides financial statements and investment data for all publicly traded Chinese manufacturing firms from 2000–2013. We construct a binary variable for commercial housing holdings to capture firm's speculative behavior and interact it with housing prices. Following prior literature (Zhou et al., 2020), we use principal component analysis (PCA) to create a composite corporate governance index based on seven indicators[10] ([10] Before conducting the PCA, we first tested whether the data were suitable. Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy: The value is 0.604. According to Kaiser's common criterion ($0.6 \leq$ KMO < 0.7 indicates "mediate suitability"), the data meet the minimum threshold for PCA. Bartlett's Test: The result is highly significant ($\chi^2 = 60150.231$, $p = 0.000$), strongly rejecting the null hypothesis that the indicators are uncorrelated. The seven indicators are as follows: executive compensation and the proportion of managerial shareholding representing incentive mechanisms; ratio of independent directors and board size capturing the board supervisory responsibility; institutional investor shareholding and equity balance reflecting the ownership structure monitoring; chairman and general manager duality indicating the general manager decision-making authority.), multiplied by –1, so higher values indicate weaker governance.

Table 8 reports the results. Columns (1)–(2) show that the interaction between ln *HP* and housing market speculation (a dummy that takes the value of 1 if a firm speculate in the real estate) is significantly negative, whether the dependent variable is adoption probability or robot value, indicating real estate diversification reduces robot adoption. Columns (3)–(4) show a negative coefficient for the inter-

Table 7. Heterogeneous effects of industry capital intensity and skill intensity.

	(1) Low capital intensity	(2) High capital intensity	(3) Full sample	(4) Low skill-intensity	(5) High skill-intensity	(6) Full sample
Panel A: Adoption probability						
ln *HP*	–0.004	–0.016***	–0.008*	–0.020**	–0.008**	–0.004
	(0.005)	(0.006)	(0.004)	(0.009)	(0.004)	(0.004)
$Capitalintensity_{high}^{Dummy}$			0.077***			
			(0.019)			
$Capitalintensity_{high}^{Dummy} \times lnHP$			–0.009***			
			(0.002)			
$Skillintensity_{high}^{Dummy}$						0.191***
						(0.025)
$Skillintensity_{high}^{Dummy} \times lnHP$						–0.022***
						(0.003)
R-squared	0.460	0.492	0.484	0.505	0.421	0.484
Panel B: Robot value						
ln *HP*	–0.045	–0.209***	–0.112**	–0.114**	–0.252**	–0.069
	(0.059)	(0.069)	(0.050)	(0.046)	(0.104)	(0.049)
$Capitalintensity_{high}^{Dummy}$			0.801***			
			(0.211)			
$Capitalintensity_{high}^{Dummy} \times lnHP$			–0.095***			
			(0.024)			
$Skillintensity_{high}^{Dummy}$						2.167***
						(0.289)
$Skillintensity_{high}^{Dummy} \times lnHP$						–0.249***
						(0.033)
R-squared	0.481	0.523	0.515	0.536	0.445	0.515
Firm controls	YES	YES	YES	YES	YES	YES
Industry controls	YES	YES	YES	YES	YES	YES
City controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	94,092	214,970	318,845	128,186	184,667	318,847

Notes: Robust standard errors in parentheses are clustered at the firm. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. The full sample contains 318,845 observations in the capital-intensity analysis and 318,847 observations in the skill-intensity analysis. This slight difference arises from different missing-data patterns in the variables used to construct the two classifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

action between ln *HP* and governance, suggesting that weak governance exacerbates the reduction. This likely reflects managerial myopia under weak governance, encouraging speculative real estate investments that crowd out robot investment.

9. Conclusion, Implications and Limitations

This paper investigates the relationship between the adoption of robots, measured by robots imported by Chinese firms, and housing prices. Theoretically, we demonstrate that high housing prices hinder firms' robot adoption through three channels: the crowding-out effect, the speculation effect, and increased labor costs. Empirically, using a 2SLS approach over the 2000–2013 period, we find that a 10% increase in housing prices reduces the probability of a firm adopting robots by 1.44 percentage points. The negative effect is particularly pronounced for firms that are highly dependent on external finance and for non-state-owned enterprises, whereas it is less severe in industries characterized by low capital intensity and skill intensity. Furthermore, firms' investments outside their core business are found to crowd out robot adoption. In environments with weak corporate governance, where managerial myopia is more prevalent, the adverse impact of high housing prices is amplified.

9.1 Implications

This study makes several theoretical implications to the literature. First, it extends the research on housing

Table 8. Different effects by housing market speculation and corporate governance.

	(1) Adoption probability	(2) Robot value	(3) Adoption probability	(4) Robot value
ln *HP*	–0.006	–0.076	–0.045*	–0.514*
	(0.030)	(0.344)	(0.024)	(0.285)
Corporate governance level			0.155	2.064*
			(0.103)	(1.248)
ln *HP* × corporate governance level			–0.020*	–0.260*
			(0.012)	(0.142)
Housing market speculation	0.427**	5.407**		
	(0.214)	(2.689)		
ln *HP* × housing market speculation	–0.048**	–0.603**		
	(0.024)	(0.305)		
Age	0.011	–0.039	–0.016	–0.122
	(0.095)	(1.177)	(0.057)	(0.694)
Size	0.038**	0.500**	0.033**	0.483***
	(0.019)	(0.230)	(0.014)	(0.164)
SOE status	–0.002	–0.004	0.013	0.184
	(0.022)	(0.268)	(0.018)	(0.218)
ROE	–0.050	–0.652	–0.030	–0.307
	(0.063)	(0.770)	(0.050)	(0.610)
Leverage ratio	–0.051	–0.559	–0.036	–0.466
	(0.058)	(0.699)	(0.048)	(0.576)
Executive shareholding ratio	0.035	0.588		
	(0.086)	(1.088)		
Constant	–0.652	–8.480	–0.146	–4.133
	(0.555)	(6.722)	(0.371)	(4.495)
R-squared	0.498	0.554	0.469	0.522
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	4412	4412	5316	5316

Notes: Robust standard errors in parentheses are clustered at the firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

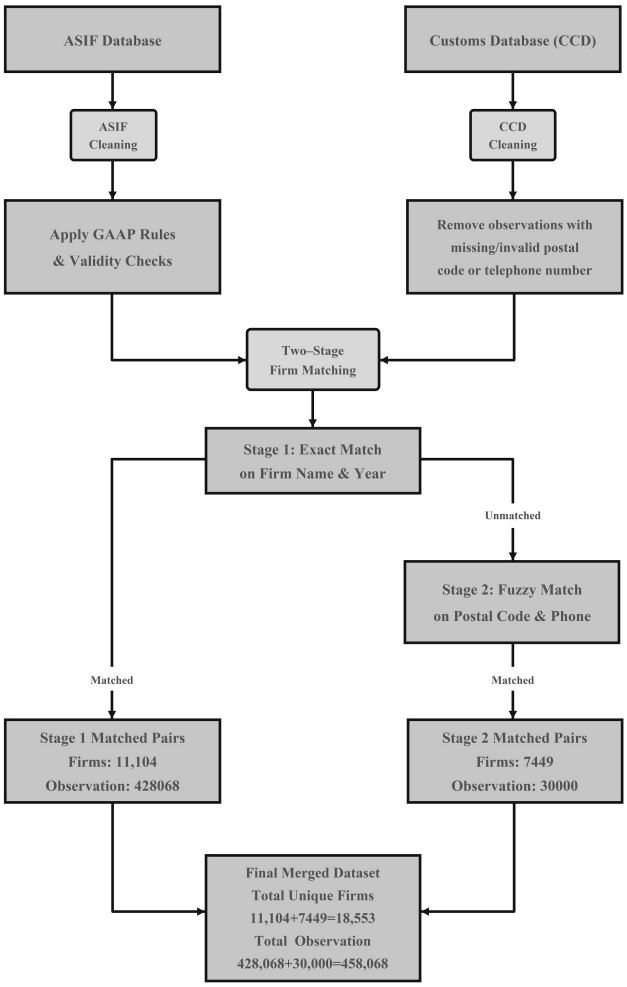


Fig. 4. The flowcharts of matching and cleaning process. GAAP, Generally Accepted Accounting Principles.

market externalities beyond traditional focuses on innovation, human capital, and entrepreneurship, providing novel micro-level evidence linking housing price to firms' automation investment decisions. Second, we identify two distinct channels—resource constraints and labor costs—through which housing prices influence technology adoption, offering an integrated theoretical framework. Third, our findings enrich agency theory by showing that real estate speculation crowds out robot adoption, particularly stronger in weak governance settings.

Against the backdrop of China's overheated housing market, our study also offers important policy implications: For policymakers, it is crucial to coordinate industrial and housing policies. This could involve stabilizing housing costs in key industrial zones and providing targeted financial support, such as subsidized loans or credit guarantee, to help manufacturers, especially private firms, invest in automation amid tight credit conditions. Firms, particularly those with weaker governance, should diversify their financing channels beyond bank loans and strengthen internal governance. For example, by linking executive compensation to long-term innovation goals, it can prevent short-term speculation from crowding out investment for technology. Financial institutions can also contribute by modernizing risk-assessment models to better account for firms' intangible assets, such as technical expertise and intellectual property, rather than relying heavily on physical collateral. This would help direct credit more efficiently toward firms committed to technological upgrading.

9.2 Limitations

This study has several limitations that future research can address. First, our data only covers 2000 to 2013. It does not include more recent years when new policies

Table 9. Definitions of main variables and data sources.

Variables	Definitions	Data sources
Dependent variable		
Robot value	The value of the robots that the firm used	CCD
Adoption probability	A dummy taking the value of 1 if the firm uses robots in production	CCD
Independent variable		
Housing prices	The logarithm of the city's commercial housing price lagged by one year	CSYRE
Firm controls		
Capital intensity	The ratio of fixed assets to employment	ASIF
Size	The logarithm of the total assets. Unit: RMB	ASIF
Export status	Equals 1 if the firm being a exporter; 0 otherwise.	ASIF
Age	Current Year- Firm's Founding Year. Unit: Year	ASIF
Industry controls		
FIE no	The logarithm of the number of foreign-invested firms	ASIF
SOE share	The ratio of the number of SOEs to the total number of domestic firms	ASIF
City controls		
GDP per capita	The logarithm of the city's GDP per capita.	CSYRE
City population	The natural logarithm of the number of registered population at the end of the year	CSYRE
City investment	The ratio of total fixed asset investment over GDP	CSYRE
Unemployment rate	The ratio of the unemployed population to the sum of the population unemployed and employed in registration	CSYRE

Notes: CCD, China Customs Database; CSYRE, China Statistical Yearbook of Regional Economy; ASIF, Annual Survey of Industrial Firms.

Table 10. Mechanisms analysis in non-state-owned enterprises.

	(1) Robot value	(2) Robot value
ln *HP*	–0.147***	–0.195***
	(0.053)	(0.049)
External finance dependence	–0.037	
	(0.034)	
External finance dependence×ln *HP*	–0.142***	
	(0.029)	
Agency cost		0.111***
		(0.025)
Agency cost×ln *HP*		0.027
		(0.036)
Constant	–1.990***	–2.336***
	(0.480)	(0.411)
Observations	255,896	312,740
R-squared	0.522	0.515
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. The controls include firm-level, industry-level, and city-level controls. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and number of foreign-invested enterprises. City-level controls include investment, population, GDP per capita, and the unemployment rate. *** $p < 0.01$.

Table 11. The Variance Inflation Factor (VIF) tests.

Variable	VIF	1/VIF
ln *HP*	3.70	0.270439
ln pergdp	3.16	0.316822
Size2	1.70	0.588140
lnKL	1.62	0.618155
Unemployment rate	1.27	0.784756
lncapital	1.26	0.791754
State ratio	1.25	0.797088
Population	1.24	0.806219
lnforeign	1.16	0.865569
Age	1.11	0.896931
Export status	1.04	0.963057
Mean VIF	1.68	

like "Made in China 2025" were introduced. Future studies could use newer data to see if the relationship between housing prices and robot adoption has changed. Second, the Annual Survey of Industrial Firms (ASIF) database only covers large and medium-sized industrial enterprises, omitting a large number of small and micro enterprises. Small firms may face even tighter financing constraints. Future research could use datasets that cover a wider range of firms. Third, we only measure imported robots, not robots made in China. This means we may not fully capture total robot adoption. As indicated in the robustness, we have also conducted robustness checks regarding the robot adoption to assess the sensitivity of our findings. The results can be found in Column 3 of Appendix Table 11. Future work could include domestic robot purchases to get a more complete picture.

Table 12. Additional robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
			Drop four industries	Excluding extreme values		
	Robot value	Robot value	Robot value	Robot value	Robot value	Robot value
Growth rate	–0.333***					
	(0.034)					
ln *HP* (residential house)		–0.175***				
		(0.049)				
ln *HP* (commercial house)			–0.239*	–0.150***	–0.118***	–0.171***
			(0.125)	(0.056)	(0.044)	(0.048)
Constant	1.834***	–1.016*	–3.190**	–1.621**	–0.828	–0.901
	(0.309)	(0.592)	(1.452)	(0.656)	(0.536)	(0.588)
Observations	315,956	318,845	85,852	240,183	319,405	318,847
R-squared	0.514	0.515	0.530	0.521	0.446	0.508
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. The controls include firm-level, industry-level, and city-level controls. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. Growth rate is measured as the annual growth rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13. The robustness for policy shocks.

	(1)	(2)
	Robot value	Robot value
ln *HP*	–0.214**	–0.141***
	(0.090)	(0.050)
ln *HP* × Year2003	0.041	
	(0.081)	
ln *HP*×Year2008		–0.064**
		(0.027)
Constant	–0.994*	–0.955
	(0.597)	(0.598)
Observations	318,847	318,847
R-squared	0.515	0.515
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. The controls include firm-level, industry-level, and city-level controls. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14. The exclusivity test for the instrumental variable.

	(1)	(2)
	Robot value	Robot value
The second stage		
ln *HP*	–2.036**	–1.677***
	(0.882)	(0.602)
Total passenger volume		–0.003
		(0.008)
Secondary industry share		0.017***
		(0.003)
Observations	318,691	318,538
The first stage		
$Slope_C^D$ ∗ Rate	0.001***	0.002***
	(0.000)	(0.000)
Cragg-Donald Wald F statistic	903.546	1990.602
Kleibergen-Paap rk Wald F statistic	466.118	904.388
Observations	318,691	318,538
Controls	YES	YES
Firm FEs	YES	YES
Year FEs	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. *** $p < 0.01$, ** $p < 0.05$.

Availability of Data and Materials

All data reported in this paper will be shared by the first author or corresponding author upon reasonable request.

Table 15. The mediating effect test for external finance constraints.

VARIABLES	(1) Robot value	(2) Interest expense ratio	(3) Robot value
ln *HP*	–0.173***	0.002***	–0.169***
	(0.049)	(0.000)	(0.049)
Interest expense ratio			–2.430***
			(0.603)
Constant	–1.026*	–0.015***	–1.062*
	(0.597)	(0.002)	(0.597)
Observations	318,622	318,622	318,622
R-squared	0.515	0.695	0.515
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. Interest expense ratio is measured as interest expenses divided by total assets. A higher value indicates a heavier financing burden. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. *** $p < 0.01$, * $p < 0.1$.

Author Contributions

RZ conceptualized the study, conducted the empirical analysis, and wrote the initial draft of the manuscript. WL contributed to the methodology, interpretation of the results, and revision of the draft. YS contributed to the conception and design of the study, interpretation of the empirical findings, and supervision. All authors contributed to critical revision of the manuscript for important intellectual content. All authors read and approved the final manuscript and agreed to be accountable for all aspects of the work.

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Conflicts of Interest

The authors declare no conflicts of interest.

Appendix

Appendix A

Data and Measurement. See Table 9, Fig. 4.

Table 16. The robustness for alternative industry skill intensity.

VARIABLES	(1) Skill intensity (2004 China census) robot value	(2) Skill intensity (1995 China census) robot value	(3) Skill intensity (1980 U.S. census) robot value
ln *HP*	–0.130**	–0.129**	–0.129**
	(0.054)	(0.054)	(0.054)
Skill intensity$_{2004}$	–0.574		
	(0.424)		
ln *HP*×skill intensity$_{2004}$	–1.080***		
	(0.268)		
Skill intensity$_{1995}$		–1.035	
		(0.789)	
ln *HP*×skill intensity$_{1995}$		–3.020***	
		(0.558)	
Skill intensity$_{1980}$			–0.738**
			(0.368)
ln *HP*×skill intensity$_{1980}$			–0.989***
			(0.212)
Constant	–1.831***	–1.878***	–1.788***
	(0.489)	(0.489)	(0.489)
Observations	245,926	245,926	245,926
R-squared	0.524	0.524	0.524
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Notes: Robust standard errors in parentheses are clustered at the firm. The controls include firm-level, industry-level, and city-level controls. Firm-level controls include firm size, firm age, capital intensity, and exporting status. Industry-level controls include the SOE share and the FIE no. City-level controls include investment, population, GDP per capita, and the unemployment rate. These census labels indicate the data sources used to construct the skill-intensity measures. *** $p < 0.01$, ** $p < 0.05$.

Appendix B

Supplementary Analysis and Sensitivity Tests. See Tables 10,11,12,13,14,15,16.

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