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HOUSING PRICE, BANK CREDIT, AND FIRM INNOVATION INVESTMENT: THEORY AND EVIDENCE FROM CHINA

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Abstract. This paper develops a novel theoretical model to explore the impact of housing price appreciation on firm innovation investment and its interaction with bank lending. The predictions of the model are empirically tested using a comprehensive dataset of China's A-share listed companies and 94 cities over the period 2011–2021. The findings provide robust evidence of a crowding-out effect, where rising housing prices negatively affect firm innovation investment. Moreover, the crowding-out effect is found to be less pronounced for firms with stronger debt repayment capabilities, superior R&D capabilities, or in tighter credit environments, consistent with the theoretical predictions. Further analysis indicates that the crowding-out effect becomes significant only when banks show a stronger preference for providing short-term loans or exhibit lower service efficiency. In terms of firm innovation outcomes, housing price appreciation generally reduces innovation efficiency, and this negative impact is especially pronounced for lower-quality innovation projects.

Keywords: housing price, bank credit, firm innovation investment.

JEL Classification: D21, G21, G32.

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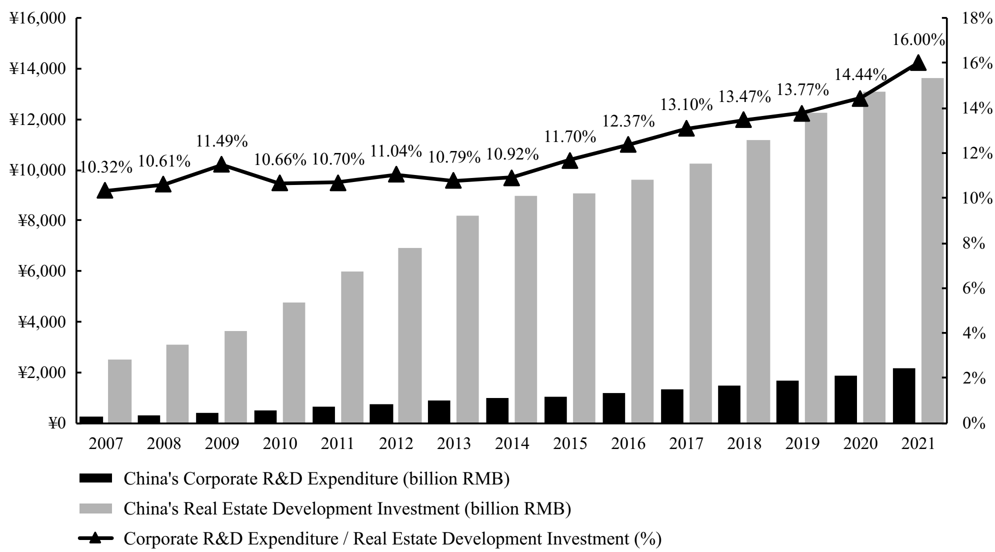
1. Introduction

China's economy is undergoing a transitional phase, shifting from rapid growth to high-quality development. Over the past few decades, China has driven its swift economic expansion primarily through increasing factor inputs, with the rapid development of the real estate market serving as a key driver of this high-speed growth. However, as the marginal returns on factor inputs diminish and the adverse effects of soaring housing prices intensify, the limitations of this development model have become increasingly apparent. In this context, innovation is regarded as a key factor in overcoming current economic development bottlenecks and achieving high-quality growth. Particularly since the 18th National Congress of the Communist Party of China in 2012, which proposed the "innovation-driven development strategy", the government has introduced a range of policies to encourage firms to engage in innovative activities. Nevertheless, compared to the short cycles, low risks, and high returns characteristics of real estate investment, innovation requires substantial long-term investment with highly uncertain returns. This discourages firms from engaging in innovative activities, resulting in prominent structural contradictions in China's economic transformation process.

These structural contradictions are clearly reflected in Figure 1. At the National Science and Technology Conference in 2006, the Chinese government proposed the strategy of independent innovation and set the goal of building an innovative nation. Shortly thereafter, the State Council issued the "National Medium- and Long-Term Program for Science and Technology Development (2006–2020)." However, the implementation of these policies has been less effective than anticipated. For a long time, national corporate R&D expenditure has remained significantly lower than real estate development investment, with the ratio of the two hovering around 10% for an extended period. Although this ratio began to rise gradually in 2014 and showed signs of accelerating after the onset of trade frictions between China and the United States in 2018, it has remained relatively low overall. Therefore, from a practical perspective, it is essential to investigate the relationship between rising housing prices and corporate innovation. This discussion will further enrich related research in the context of China's economic transformation.

Recent studies have documented both the positive and negative impacts of housing price increases on firms' innovation activities. The "collateral enhancement view," as well documented in the literature (e.g., Cooper, 2013; Chen et al., 2015; Mao, 2021), argues that real estate serves as a critical form of collateral for firms when borrowing from banks or other lenders. Consequently, housing price appreciations enhance a firm's collateral value, thereby increasing its external financing capacity and fostering greater investment in innovation. Conversely,



Note: The figure illustrates the temporal trends in China's real estate development investment and corporate Research and Development (R&D) expenditure from 2007 to 2021. The gray dashed bars represent the annual total of real estate development investment, while the black bars indicate the annual total of corporate R&D expenditure. The line with markers depicts the ratio of corporate R&D expenditure to real estate development investment over the same period. The data are sourced from the Wind Database.

Figure 1. Trend of China's real estate development investment and corporate R&D expenditure

researches supporting the "investment opportunity view" (e.g., Miao & Wang, 2014; Rong et al., 2016; Lu et al., 2019) provide evidence that housing price booms can lead firms to divert funds toward real estate investments, reducing their resources available for innovation.

Despite these contrasting perspectives and findings, two key issues remain unresolved. First, while there is a wealth of empirical studies examining the relationship between housing prices and firm innovation, theoretical studies modeling the "housing price appreciation–firm innovation investment" nexus and its underlying mechanisms are still underdeveloped. Second, given the competing views and mixed results in the existing literature, further empirical studies are needed to clarify the dominant effect of housing price appreciation on firm innovation investment. Moreover, although a substantial body of empirical research highlights the role of financing constraints in hindering firms' innovation investment, little is known about how this occurs, as explicit modeling of bank behavior is lacking.

Motivated by the inadequacies of the existing literature, this paper attempts to address these unresolved issues through both theoretical analysis and empirical testing. The main contributions of this paper are twofold.

On the theoretical front, we develop a simple yet insightful model to examine how housing price appreciation influences firms' investment behavior and how this process interacts with bank lending. In the model, firms allocate limited resources between housing and innovation investment, while oligopolistic banks determine lending rates for firms. We first characterize the uncertainty of innovation investment, emphasizing its high-risk, high-return nature in contrast to the lower-risk profile of real estate investment. Building on this foundation, we explore the role of the banking sector as a financial intermediary in managing risk and supervising firms' investment decisions. The interaction mechanisms between firms and banks are multifaceted: banks set lending rates based on firms' prior financial performance and investment behavior, while these lending rates, in turn, influence firms' investment decisions and their subsequent innovation activities. By modeling this dynamic process, we explicitly highlight the critical role of the banking sector in shaping firms' innovation investment.

On the empirical front, we test the theoretical predictions of the model using a dataset of firms and cities in China, a country that has experienced a significant housing price boom over the past two decades, particularly following the 2008 Global Financial Crisis. Our findings contribute to several major strands of literature on housing price appreciation and firm innovation.

First, regarding the debate on the collateral versus crowding-out effects of housing price appreciation on firm investment (e.g., Gan, 2007; Chaney et al., 2012; Chakraborty et al., 2018; Wu et al., 2020; Martín et al., 2021; Beracha et al., 2022; Kjenstad & Kumar, 2022) and firm innovation (e.g., Jia et al., 2021; Beracha et al., 2022), our study supports the "investment opportunity view" by providing robust evidence that housing price appreciation exerts a crowding-out effect on firm innovation investment. Furthermore, we find that this crowding-out effect is mitigated for firms with stronger debt repayment capabilities or superior R&D capabilities.

Second, our study contributes to the emerging literature on the impact of economic policies on firm innovation (e.g., Zwick & Mahon, 2017; Guceri & Liu, 2019; Duong et al., 2020; Giebel & Kraft, 2020; Contreras et al., 2021) by demonstrating that the crowding-out effect of housing price appreciation on firm innovation investment is alleviated under tighter credit environments. This finding underscores the importance of financial conditions in the relationship between housing price appreciation and firm innovation investment, simultaneously reinforcing the growing literature on the finance–real economy nexus, which highlights the pivotal role of financial systems in shaping real economic activity.

The remainder of the paper is organized as follows. Section 2 introduces the model and presents the theoretical analysis. Section 3 outlines the research design for the empirical investigation. Section 4 tests the theoretical predictions derived in Section 2. Section 5 offers additional insights into the role of banks and firm innovation efficiency. Finally, Section 6 concludes with a discussion of policy implications and research limitations.

2. The model

In this Section, we construct a highly stylized model to illustrate the key mechanisms underlying the relationship among housing prices, bank credit, and firm innovation investment. The model involves two types of agents: (1) the firm, which allocates limited resources between innovation activities and real estate investment, and (2) the bank, which collects public deposits and provides loans to firms.

To start with, we follow the standard literature by assuming that the firm produces with a Cobb-Douglas (C-D) function:

$$Y_i = A_i K_i^{\alpha} N_i^{\beta}, \tag{1}$$

where Y_i denotes the output of firm i, A_i, K_i and N_i denote the firm's productivity, capital and labor, respectively, α and β denote the capital income share and labor income share, respectively.

To explicitly illustrate how firm innovation investment influences output through the productivity channel, we assume that a firm's productivity is a function of its innovation investment, expressed in the following form:

$$A_i = A_{i0}\left[\left(1+a_i\right)p(I_i^{RD}) + \left(1-p(I_i^{RD})\right)\right] = A_{i0}\left(1+a_i p(I_i^{RD})\right), \tag{2}$$

where A_{i0} and I_i^{RD} denote the initial level of productivity and the innovation investment (captured by R&D expenditures) of firm i, respectively.

Eq. (2) represents firm i's expected productivity level resulting from its innovation activities. Given the high uncertainty and risk inherent in innovation, these activities are subjected to a probability $p(I_i^{RD})$ $(0 \le p(I_i^{RD}) \le 1)$ of success. If the firm successfully innovates, its productivity improves by a_i. Conversely, if the innovation fails, the firm experiences no productivity gains and retains its previous productivity level.

Typically, the probability of innovation success ($p(I_i^{RD})$) is positively correlated with the firm's R&D intensity ($\frac{I_i^{RD}}{K_i}$) and R&D capability (ϖ_i). Accordingly, we define $p(I_i^{RD})$ in the following form:

$$p(I_i^{RD}) = \phi(\varpi_i)\left(\frac{I_i^{RD}}{K_i}\right)^{\gamma}, \tag{3}$$

where γ denotes the elasticity of the innovation success probability with respect to R&D intensity. Existing studies (Hall et al., 1986; Blundell et al., 2002; Klette & Kortum, 2004; Acemoglu et al., 2018) suggest that $\gamma \in (0,1)$, indicating that as the firm's R&D intensity increases, the improvement in its innovation success probability gradually decreases, reflecting the principle of diminishing marginal returns on innovation investment. $\phi(\varpi_i)$ captures the non-linear relationship between the firm's R&D capability and its innovation success probability. It is reasonable to assume that $\phi(\varpi_i)$ is an increasing function of the firm's R&D capability. Thus, we have $\frac{\partial \phi(\varpi_i)}{\partial \varpi_i} > 0$.

Eqs. (2)–(3) suggest that when a firm increases its innovation investment, its probability of innovation success rises, leading to a higher expected productivity level. Furthermore, the improvements in both the innovation success probability and the expected productivity level are more pronounced in firms with superior R&D capabilities.

Publicly listed companies can engage in real estate investment through various channels. First, a company may directly purchase real estate assets. Second, it can invest in financial products backed by real estate as the underlying asset. Third, it may indirectly invest in real estate by acquiring shares, forming joint ventures, engaging in mergers and acquisitions, or establishing subsidiaries or branches. Lastly, the parent company or controlling shareholders may leverage the company's resources for real estate investment through related-party transactions. The latter three channels are indirect and often covert, making it challenging to fully capture the company's real estate investment activities through its financial statements. Nevertheless, regardless of the specific channel used, the profit mechanism remains consistent, as gains are primarily derived from the appreciation of real estate prices.

Given that the rapid increase in housing prices has been one of the most significant drivers of the prosperity in China's real estate market, and that city-level housing price data are more comprehensive and readily accessible through public sources, the subsequent theoretical and empirical analyses will focus primarily on firms' housing investments. Furthermore, to maintain focus on the primary objective of this paper – namely, examining how changes in housing prices influence firms' innovation – we simplify the analysis by not distinguishing between specific channels of real estate investment.

The firm needs to optimally allocate its planned investment scale, denoted as $\overline{C}_i$, between housing investment (I_i^H) and innovation investment (I_i^{RD}) to maximize profits. The rate of return on the firm's housing investment, driven by the increase in housing prices[1], is denoted as r_h. The firm's planned investment scale $\overline{C}_i$ is sourced from two avenues: equity E_i and bank credit L_i. To ensure that bank credit plays a role in the firm's investment, we assume that equity alone is insufficient to finance the firm's total investment in housing and innovation. For simplicity, and without loss of generality, we assume that the firm's equity can finance only a fraction $\chi(r^*, r_h)$ $(0 < \chi(r^*, r_h) < 1)$ of its total investment, i.e., $E_i = \chi(r^*, r_h)(I_i^{RD} + I_i^H)$, with the remainder financed through bank credit, i.e., $L_i = (1 - \chi(r^*, r_h))(I_i^{RD} + I_i^H)$. The amount of bank credit L_i and the corresponding lending rate r_i^L are determined by the bank's optimal lending decision.

[1] In our model, the return on housing investment is assumed to be mainly from the rising housing price, which is also the main source of return on housing investment in China. Thus, for simplicity we do not consider the return on rental activities here. However, including an additional term of "rental return" in our model would not change the main results of the paper.

It is important to note that, although the firm's equity is assumed to be insufficient to cover its entire planned investment scale, this does not imply that the firm will allocate all of its equity to investment. Firms have both the willingness and the ability to adjust the financing structure of their investments. On the one hand, the overall credit environment influences the proportion of credit financing in firms' investments. When credit is more readily available, firms can obtain bank loans at lower costs, leading to a higher proportion of credit financing. The policy interest rate (r^*) typically measures the tightness of the credit environment, with a higher policy interest rate indicating a tighter credit environment. Therefore, we have $\frac{\partial \chi\left(r^*, r_h\right)}{\partial r^*} > 0$. On the other hand, compared to innovation investment, housing investment is often considered low-risk, and real estate is a common form of high-quality collateral for bank credit. Consequently, when housing prices appreciate, firms are more likely to increase the proportion of credit financing allocated to housing investment, i.e., $\frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} < 0$.

In addition to investing in real estate and innovation activities, firms must allocate resources to acquire capital K_i and hire labor N_i for production. Capital typically refers to fixed assets such as machinery, equipment, factory buildings, and infrastructure. Acquiring or constructing these assets often requires substantial time and financial resources, making it difficult for firms to adjust their capital levels rapidly in the short run. Therefore, we assume that capital K_i is an exogenous production factor in the short run. In contrast, labor input is more flexible, as firms can easily increase labor through overtime work or by hiring temporary workers. As a result, when solving the firm's optimization problem, labor N_i is treated as an endogenous variable.

The firm's optimization problem is expressed as follows:

$$\begin{aligned} \underset{\{I_i^{RD}, N_i\}}{\text{Max}} \ \Pi_i &= \left\{A_{i0}\left(1 + a_i p(I_i^{RD})\right) K_i^{\alpha} N_i^{\beta}\right\} - W_i N_i + r_h I_i^H - r_i^L L_i \\ \text{s.t.} \quad L_i &= \left(1 - \chi\left(r^*, r_h\right)\right) \overline{C}_i \\ \overline{C}_i &= I_i^{RD} + I_i^H, \end{aligned} \tag{4}$$

where Π_i represents the profits of firm i, W_i denotes unit labor wage, and the price of the firm's product is normalized to 1. Eq. (4) shows that the firm's revenue consists of income from its main business operations and returns on housing investment, while its expenses include labor wages and loan interest payments.

As is common in the literature, we assume the presence of a representative bank j that raises funds by absorbing public deposits D_j and issuing equity B_j to finance loans to the firms L_j. Following Dell'Ariccia et al. (2017), we simplify by assuming that deposits are fully insured, and thus the cost of deposits (i.e., the interest rate paid on deposits) is normalized to the monetary policy rate r^*. Due to information asymmetry between the bank and firms, the bank primarily relies on a firm's historical financial performance to assess its future cash flows ($flow_i$) and, consequently, its probability of timely repayment $d\left(flow_i\right)$. When a firm repays on time, the bank recovers both the principal and interest $(1 + r_i^L)L_{ji}$. However, if a firm defaults, its intangible assets derived from innovation investment are difficult to liquidate or heavily discounted. In such cases, the bank can only liquidate the firm's real estate assets, recovering $m_i\left(I_i^{RD},r_h\right)$ $\left(0<m_i\left(I_i^{RD},r_h\right)<1\right)$ fraction of the granted loans. Therefore, we have $\frac{\partial m_i\left(I_i^{RD},r_h\right)}{\partial I_i^{RD}}<0$ and $\frac{\partial m_i\left(I_i^{RD},r_h\right)}{\partial r_h}>0$. This implies that when firms allocate more funds to innovation investment, they may face more stringent financing constraints due to the lack of high-quality collateral, which aligns with real-world observations. Furthermore, the bank incurs management costs ΦL_{ji} $\left(0<\Phi<1\right)$ when granting loans.

China's banking sector is characterized by a highly concentrated market structure, with the Big Four state-owned commercial banks dominating in terms of scale and deposit-lending business (Bailey et al., 2011; Allen et al., 2005). In such an oligopolistic market, banks possess relatively strong bargaining power over firms, enabling them to dominate loan contracts and adopt differentiated pricing strategies based on firms' financial performance and risk profiles (Ye et al., 2012; Gomez-Gonzalez et al., 2023). To better capture these characteristics of China's banking sector, we assume that the bank can independently calculate the costs and profits associated with each loan. The bank's optimization problem is to maximize its profits subject to the balance sheet constraint:

$$\begin{aligned}&\underset{\{L_{ji}\}}{\text{Max}}\ \Pi_{ji}^{B}=d\left(flow_i\right)(1+r_i^L)L_{ji}+\left(1-d\left(flow_i\right)\right)m_i\left(I_i^{RD},r_h\right)L_{ji}-(1+r^*)D_{ji}-B_{ji}-\Phi L_{ji}\\&\qquad\text{s.t.}\quad L_{ji}=D_{ji}+B_{ji},\end{aligned}\tag{5}$$

where Π_j^B denotes the bank's profits.

The first-order condition with respect to bank lending is expressed as follows:

$$r_i^L=\frac{1+r^*+\Phi-\left(1-d\left(flow_i\right)\right)m_i\left(I_i^{RD},r_h\right)}{d\left(flow_i\right)}-1.\tag{6}$$

Eq. (6) indicates that the bank will set higher lending rates for firms with higher default risks ($1-d\left(flow_i\right)$) and lower loan recovery rates ($m_i\left(I_i^{RD},r_h\right)$).

Solving the firm's optimization problem (Eq. (4)) yields the following first-order conditions for the firm's optimal labor input (N_i^*) and innovation investment (I_i^{RD*}), respectively:

$$N_i^*=\left[\frac{W_i}{\beta A_{i0}\left(1+a_ip(I_i^{RD})\right)K_i^{\alpha}}\right]^{\frac{1}{\beta-1}};\tag{7}$$

$$\frac{A_{i0}a_i\gamma p(I_i^{RD*})K_i^{\alpha}N_i^{*\beta}}{I_i^{RD*}}=r_h-\left(1-\chi\left(r^*,r_h\right)\right)\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\frac{\partial m_i\left(I_i^{RD},r_h\right)}{\partial I_i^{RD}}\overline{C}_i.\tag{8}$$

Eq. (7) represents the labor demand equation, indicating that the firm's optimal labor input is achieved when the marginal cost of labor equals its marginal benefit. Eq. (8) represents the firm's innovation investment demand equation, which shows that the optimal level of innovation investment is achieved when the marginal return on innovation investment equals the sum of the return on housing investment and the marginal increase in credit cost incurred by innovation investment. By substituting Eq. (7) into Eq. (8), we derive the following Equation:

$$\frac{A_{i0}a_i\gamma p(I_i^{RD*})K_i^{\alpha}\left[\frac{W_i}{\beta A_{i0}\left(1+a_ip(I_i^{RD*})\right)K_i^{\alpha}}\right]^{\frac{\beta}{\beta-1}}}{I_i^{RD*}}-r_h+\left(1-\chi\left(r^*,r_h\right)\right)\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\overline{C}_i=0. \tag{9}$$

To examine how changes in housing price affect firms' innovation investment, we calculate the partial derivative of Eq. (9) with respect to housing price growth rate (r_h), which yields[2]:

$$\frac{\partial I_i^{RD*}}{\partial r_h}=\frac{1+\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i-\left(1-\chi\left(r^*,r_h\right)\right)\frac{\partial^2 m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}\partial r_h}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i}{G_i\left\{\gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_ip(I_i^{RD*})\right)^{-1}a_ip(I_i^{RD*})\right]-1\right\}}, \tag{10}$$

where $G_i=a_i\gamma\phi(\varpi_i)\left(A_{i0}\right)^{1-\frac{\beta}{\beta-1}}\beta^{-\frac{\beta}{\beta-1}}K_i^{\alpha-\gamma-\frac{\alpha\beta}{\beta-1}}\left(W_i\right)^{\frac{\beta}{\beta-1}}\left(1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right)^{-\frac{\beta}{\beta-1}}(I_i^{RD*})^{\gamma-2}$.

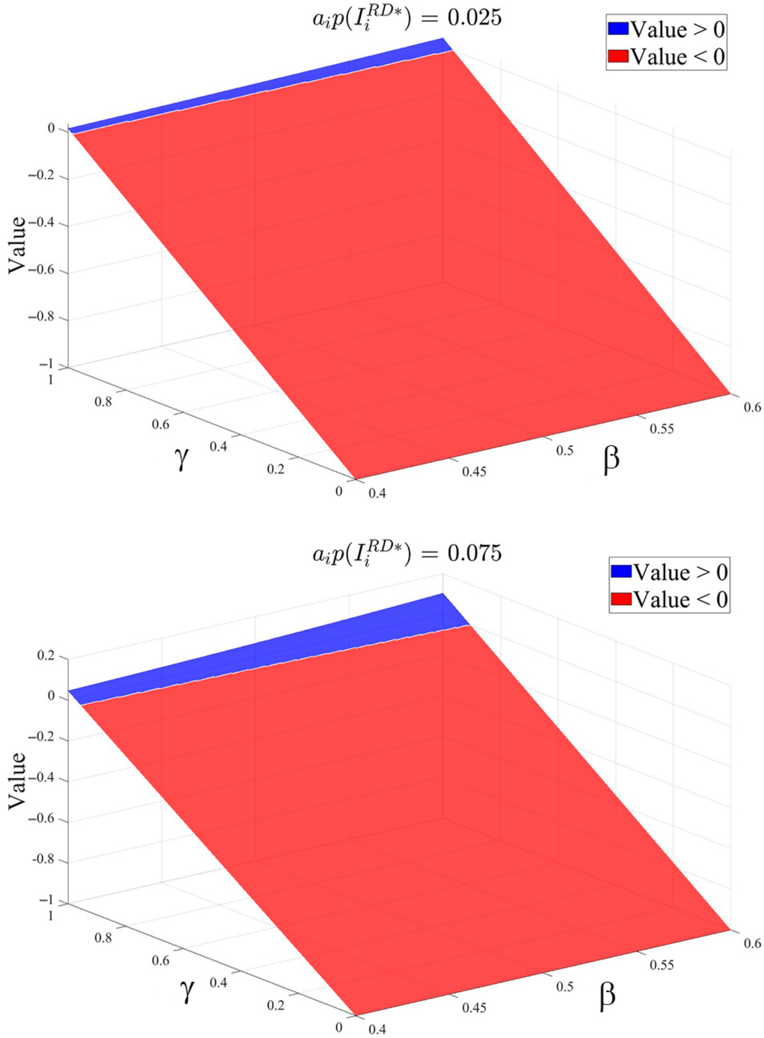
Since the effects of changes in innovation investment and the rate of return on housing investment on the bank's loan recovery rate are independent of each other, we have $\frac{\partial^2 m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}\partial r_h}=0$. Thus, Eq. (10) simplifies to the following:

$$\frac{\partial I_i^{RD*}}{\partial r_h}=\frac{1+\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i}{G_i\left\{\gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_ip(I_i^{RD*})\right)^{-1}a_ip(I_i^{RD*})\right]-1\right\}}. \tag{11}$$

According to the definitions in the theoretical model, all components in G_i are greater than 0, thus $G_i > 0$. Moreover, previous analysis reveals that $\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}<0$, $\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}<0$, $\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}>0$, and $\overline{C}_i>0$. Therefore, the numerator in Eq. (11) is greater than 0, and the sign of Eq. (11) primarily depends on the sign of H_i, $H_i=\gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_ip(I_i^{RD*})\right)^{-1}a_ip(I_i^{RD*})\right]-1$.

In the existing literature, the labor income share (β) typically ranges from 0.4 to 0.6 (Lee & Song, 2015; Bi et al., 2016; Ma & Jiang, 2023), while the expected level of productivity improvement, denoted as $a_ip(I_i^{RD*})$, generally does not exceed 2.5% (Solow, 1957; Jorgenson & Griliches, 1967; Smets & Wouters, 2007). Regarding innovation elasticity (γ), although the literature consistently agrees that $\gamma\in\left(0,1\right)$, there is ongoing debate about its specific value. Reported values of γ typically range from 0.3 to 0.7, with 0.5 being a common benchmark (Hall et al., 1986; Blundell et al., 2002; Acemoglu et al., 2018). After determining the range of relevant parameters, we further calculate the value of H_i, as shown in Figure 2.

[2] The detailed derivation process is presented in Appendix.



Note: This figure presents the values of H_i, $H_i = \gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_i p(I_i^{RD*})\right)^{-1} a_i p(I_i^{RD*})\right]-1$, when the labor income share β and innovation elasticity γ change within their realistic ranges. The left panel displays the results for the scenario where $a_i p(I_i^{RD*})$ is 2.5%, while the right panel shows the scenario where $a_i p(I_i^{RD*})$ is 7.5%.

Figure 2. Values of H_i on the realistic ranges of relevant parameters

The expected productivity improvement $a_i p(I_i^{RD*})$ in specific industries may surpass the overall average. For instance, during the 1990s, the Total Factor Productivity (TFP) growth rate in the U.S. Information Technology (IT) industry reached up to 4%. Consequently, we examine two scenarios where $a_i p(I_i^{RD*})$ takes values of 2.5% and 7.5% to strengthen the robustness of our conclusions. The results in the left panel of Figure 2 indicate that when $a_i p(I_i^{RD*})$ takes the value of 2.5%, H_i is greater than 0 only when γ approaches 1. According to the right panel of Figure 2, when $a_i p(I_i^{RD*})$ is 7.5%, γ must still exceed 0.9 for H_i to be greater than 0. Clearly, after considering the realistic range of relevant parameters, we can conclude that $H_i < 0$.

With $H_i < 0$, it is evident that $\frac{\partial I_i^{RD*}}{\partial r_h} < 0$. This suggests that, all else being equal, the firm's optimal innovation investment decreases as the rate of return on housing investment (i.e., housing price appreciation) rises. The result is straightforward: greater housing price appreciation makes housing investment more profitable for the firm, thereby increasing the opportunity cost of innovation investment and making it less attractive. Consequently, the firm reallocates funds from innovation investment to housing investment. The greater the housing price appreciation, the more innovation investment is crowded out by housing investment. Thus, we arrive at **Proposition 1.**

Proposition 1. *Housing price appreciation has a crowding-out effect on the firm's innovation investment.*

After examining the impact of housing price appreciation on the firm's innovation investment, we proceed to discuss how other variables in the model may affect the firm's innovation investment through the housing price channel. This analysis helps us to understand the potential heterogeneities in the "housing price-innovation investment" relationship across firms with different characteristics and under varying financial conditions. To this end, we calculate the partial derivatives of Eq. (11) with respect to various firm-specific and financial variables.

From Eq. (11), it can be observed that the probability of the firm's timely repayment ($d\left(flow_i\right)$) affects the crowding-out effect of housing price appreciation on the firm's innovation investment through the bank lending rate (r_i^L). As previously analyzed, the bank assesses this probability based on the firm's future cash flows, which serve as an effective measure of its debt repayment capabilities. The stronger the firm's debt repayment capability, the higher the probability the bank assigns to the firm repaying the loan on time. Therefore, assuming the firm's debt repayment capability is denoted as θ_i, we have $\frac{\partial d\left(flow_i\right)}{\partial \theta_i} > 0$. Solving the second-order partial derivative of Eq. (11) with respect to θ_i yields:

$$\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial \theta_i} = \frac{-\frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} \frac{\partial m_i\left(I_i^{RD*}, r_h\right)}{\partial I_i^{RD*}} d^{-2}\left(flow_i\right) \frac{\partial d\left(flow_i\right)}{\partial \theta_i} \overline{C}_i}{G_i\left\{\gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_i p(I_i^{RD*})\right)^{-1} a_i p(I_i^{RD*})\right]-1\right\}}. \tag{12}$$

Since $\frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} < 0$, $\frac{\partial m_i\left(I_i^{RD*}, r_h\right)}{\partial I_i^{RD*}} < 0$, $\frac{\partial d\left(flow_i\right)}{\partial \theta_i} > 0$, $d\left(flow_i\right) > 0$, $\overline{C}_i > 0$, $G_i > 0$, and $H_i = \gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_i p(I_i^{RD*})\right)^{-1} a_i p(I_i^{RD*})\right]-1 < 0$, we have $\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial \theta_i} > 0$. This suggests that, all else being equal, the crowding-out effect of housing price appreciation on innovation investment is less pronounced in firms with stronger debt repayment capabilities.

Typically, firms with larger output scales possess more fixed assets, which can be used as collateral for bank loans, thereby reducing the bank's default risk. Furthermore, firms with larger output scales often have longer operating histories and higher market shares, which contribute to sustained profitability and abundant cash flows. As a result, it can be inferred that firms with larger output scales exhibit stronger debt repayment capabilities. Additionally, State-Owned Enterprises (SOEs) are generally perceived as having stronger debt repayment capabilities than Non-State-Owned Enterprises (non-SOEs), due to implicit government credit support. Thus, we have **Proposition 2.**

Proposition 2. *The crowding-out effect of housing price appreciation on innovation investment is mitigated in firms with larger output scales or stated-owned ownership, as they possess stronger debt repayment capabilities.*

The firm's R&D capability (ϖ_i) may influence its investment decisions, thereby affecting the crowding-out effect of housing price appreciation on innovation investment. By solving the second-order partial derivative of Eq. (11) with respect to ϖ_i, we obtain:

$$\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial \varpi_i} = \left[1 + \frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} \frac{\partial m_i\left(I_i^{RD*}, r_h\right)}{\partial I_i^{RD*}} \frac{\left(1 - d\left(flow_i\right)\right)}{d\left(flow_i\right)} \overline{C}_i\right]\left(H_i^{-1} \frac{\partial G_i^{-1}}{\partial \varpi_i} + G_i^{-1} \frac{\partial H_i^{-1}}{\partial \varpi_i}\right). \quad (13)$$

Since $\left[1 + \frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} \frac{\partial m_i\left(I_i^{RD*}, r_h\right)}{\partial I_i^{RD*}} \frac{\left(1 - d\left(flow_i\right)\right)}{d\left(flow_i\right)} \overline{C}_i\right]$ in Eq. (13) is greater than 0, the sign of Eq. (13) depends on the sign of $\left(H_i^{-1} \frac{\partial G_i^{-1}}{\partial \varpi_i} + G_i^{-1} \frac{\partial H_i^{-1}}{\partial \varpi_i}\right)$. Let $F_i = a_i \gamma \phi(\varpi_i)\left(A_{i0}\right)^{1-\frac{\beta}{\beta-1}} \beta^{-\frac{\beta}{\beta-1}} K_i^{\alpha-\gamma-\frac{\alpha\beta}{\beta-1}} \left(W_i\right)^{\frac{\beta}{\beta-1}}$, and then solve for the partial derivative of G_i^{-1} with respect to ϖ_i:

$$\frac{\partial G_i^{-1}}{\partial \varpi_i} = (I_i^{RD*})^{2-\gamma} \frac{F_i^{-1}}{\phi(\varpi_i)} \frac{\partial \phi(\varpi_i)}{\partial \varpi_i}\left[1 + a_i p(I_i^{RD*})\right]^{\frac{1}{\beta-1}} \left[\frac{a_i p(I_i^{RD*})}{\beta - 1} - 1\right]. \quad (14)$$

Next, we solve for the partial derivative of H_i^{-1} with respect to ϖ_i as follows:

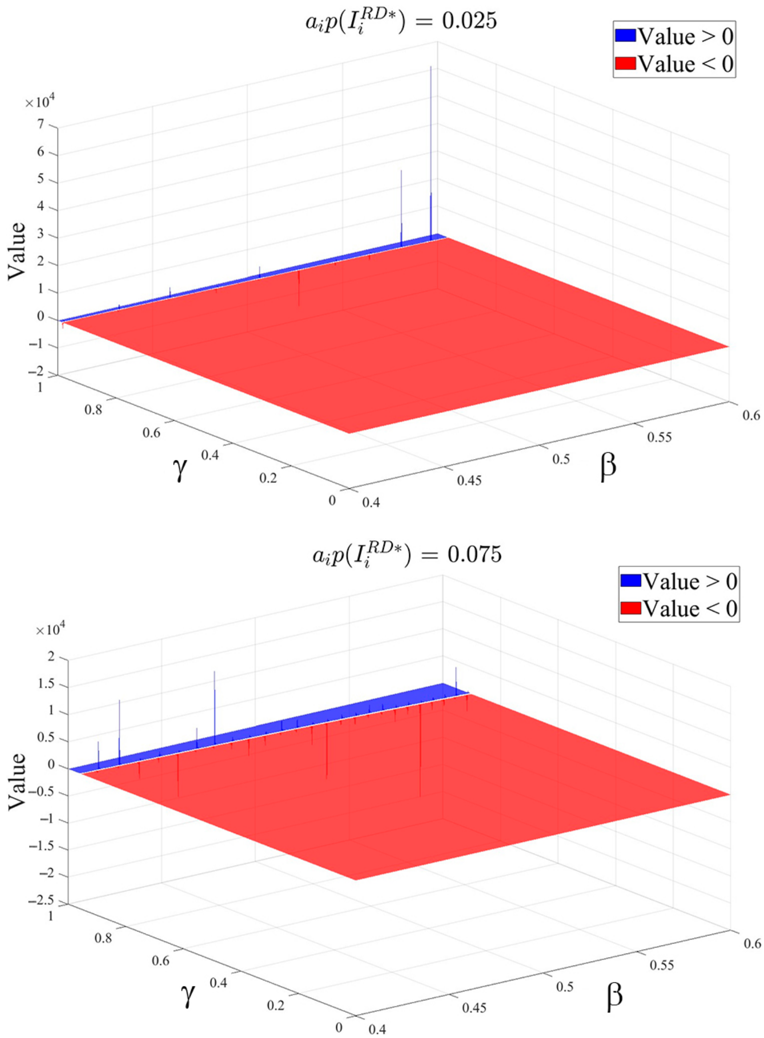
$$\frac{\partial H_i^{-1}}{\partial \varpi_i} = -H_i^{-2} \times \left\{\frac{\gamma\beta}{1-\beta} \frac{a_i p(I_i^{RD*})}{\left(1 + a_i p(I_i^{RD*})\right)\phi(\varpi_i)} \frac{\partial \phi(\varpi_i)}{\partial \varpi_i}\left[1 - \frac{a_i p(I_i^{RD*})}{1 + a_i p(I_i^{RD*})}\right]\right\}. \quad (15)$$

Then, we can rewrite the expression for $\left(H_i^{-1} \frac{\partial G_i^{-1}}{\partial \varpi_i} + G_i^{-1} \frac{\partial H_i^{-1}}{\partial \varpi_i}\right)$ as follows:

$$H_i^{-1} \frac{\partial G_i^{-1}}{\partial \varpi_i} + G_i^{-1} \frac{\partial H_i^{-1}}{\partial \varpi_i} = H_i^{-1} G_i^{-1} \frac{1}{\phi(\varpi_i)} \frac{\partial \phi(\varpi_i)}{\partial \varpi_i} J_i, \quad (16)$$

where $J_i = \frac{\beta}{\beta-1} \frac{a_i p(I_i^{RD*})}{1 + a_i p(I_i^{RD*})}\left[1 + H_i^{-1}\gamma\left(1 - \frac{a_i p(I_i^{RD*})}{1 + a_i p(I_i^{RD*})}\right)\right] - 1$. As shown in Figure 3, when the relevant parameters (i.e., β, γ, and $a_i p(I_i^{RD*})$) vary within their realistic ranges, the values of J_i are generally less than 0.

According to previous definitions and analysis, we have $H_i^{-1} < 0$, $G_i^{-1} > 0$, $\frac{\partial \phi(\varpi_i)}{\partial \varpi_i} > 0$, and $J_i < 0$. Consequently, we conclude that $\left(H_i^{-1} \frac{\partial G_i^{-1}}{\partial \varpi_i} + G_i^{-1} \frac{\partial H_i^{-1}}{\partial \varpi_i}\right) > 0$, and thus $\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial \varpi_i} > 0$. This suggests that, all else being equal, the crowding-out effect of housing price appreciation on innovation investment is less pronounced in firms with better R&D capabilities. As implied by Eqs. (2)–(3), better R&D capabilities lead to greater improvements in the firm's productivity,



Note: This figure presents the values of J_i, $J_i = \frac{\beta}{\beta-1}\frac{a_i p(I_i^{RD*})}{1+a_i p(I_i^{RD*})}\left[1+H_i^{-1}\gamma\left(1-\frac{a_i p(I_i^{RD*})}{1+a_i p(I_i^{RD*})}\right)\right]-1$, when the labor income share β and innovation elasticity γ change within their realistic ranges. The left panel displays the results for the scenario where $a_i p(I_i^{RD*})$ is 2.5%, while the right panel shows the scenario where $a_i p(I_i^{RD*})$ is 7.5%.

Figure 3. Values of J_i on the realistic ranges of relevant parameters

which boosts the firm's main business revenues and thereby reduces the attractiveness of housing investment. This aligns with reality, as firms with superior R&D capabilities typically derive their competitive advantages from continuous innovation. Therefore, even if these firms have the opportunity to invest in high-return assets like real estate, they are unlikely to substantially cut back on innovation investment, as doing so could weaken their competitiveness and long-term viability. Based on this reasoning, we propose **Proposition 3.**

Proposition 3. *The crowding-out effect of housing price appreciation on innovation investment is mitigated in firms with better R&D capabilities.*

To examine how the credit environment may influence the impact of housing price appreciation on firm innovation investment, we calculate the second-order partial derivative of Eq. (11) with respect to the policy interest rate r^*:

$$\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial r^*} = \frac{\dfrac{\partial^2 \chi\left(r^*, r_h\right)}{\partial r_h \partial r^*} \dfrac{\partial m_i\left(I_i^{RD*}, r_h\right)}{\partial I_i^{RD*}} \dfrac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)} \overline{C}_i}{G_i\left\{\gamma\left[1+\dfrac{\beta}{1-\beta}\left(1+a_i p(I_i^{RD*})\right)^{-1} a_i p(I_i^{RD*})\right]-1\right\}}. \tag{17}$$

It is evident that the sign of Eq. (17) depends on the sign of $\frac{\partial^2 \chi\left(r^*, r_h\right)}{\partial r_h \partial r^*}$. Although previous analysis concluded that $\frac{\partial \chi\left(r^*, r_h\right)}{\partial r^*} > 0$ and $\frac{\partial \chi\left(r^*, r_h\right)}{\partial r_h} < 0$, these results do not directly determine the sign of $\frac{\partial^2 \chi\left(r^*, r_h\right)}{\partial r_h \partial r^*}$, which requires further discussion. The impact of housing price appreciation r_h on the firm's financing structure $\chi\left(r^*, r_h\right)$ is evidently related to the policy interest rate r^*. When the firm invests in real estate using funds sourced from bank credit, the net return on this investment equals the difference between the housing price appreciation r_h and the bank lending rate r_i^L. As the credit environment tightens, indicated by an increase in the policy interest rate r^*, returns on financial assets such as real estate decrease due to reduced market liquidity (Cox & Ludvigson, 2021). Additionally, the bank will raise lending rates r_i^L in response to higher policy interest rates r^*, as implied by Eq. (6). Consequently, the net return diminishes under a tighter credit environment, discouraging firms from increasing bank credit financing to invest in real estate. Therefore, we have $\frac{\partial^2 \chi\left(r^*, r_h\right)}{\partial r_h \partial r^*} > 0$.

With $\frac{\partial^2 \chi\left(r^*, r_h\right)}{\partial r_h \partial r^*} > 0$, we obtain $\frac{\partial^2 I_i^{RD*}}{\partial r_h \partial r^*} > 0$. This indicates that, all else being equal, the crowding-out effect of housing price appreciation on firm innovation investment is mitigated under tighter credit environments, represented by increases in the policy interest rate. This result is intuitive: in a tighter credit environment, the costs of bank credit rise, and the returns on housing investment decrease, thereby discouraging firms from investing in real estate. Based on this reasoning, we propose **Proposition 4.**

Proposition 4. *The crowding-out effect of housing price appreciation on firm innovation investment is mitigated under tighter credit environments.*

3. Research design

In the theoretical model, we analyzed the relationship between housing price appreciation and firm innovation, as well as its potential variations across different firm characteristics and financial conditions, resulting in four testable propositions. In this section, we outline the research design employed to empirically test these theoretical predictions.

3.1. Sample and data

3.1.1. The evolution of China's housing market and innovation activities

China serves as an exemplary case study for the primary issue addressed in this paper. Since 1998, China's housing market has undergone unprecedented growth, transitioning from a system of distributing free housing to government employees to the establishment of a competitive housing market. National real estate development investment increased from 1,942.29 billion RMB in 2006 to 13,627.52 billion RMB in 2021, reflecting an average annual growth rate of 15.05%. During the same period, the average price of commercial housing surged from 3,366.79 RMB/m^2 in 2006 to 10,322.67 RMB/m^2 in 2021, with an average annual growth rate of 7.79%.

Simultaneously, China's innovation activities have been significantly reinforced, particularly since the National Science and Technology Conference in 2006 and the 18th National Congress of the Communist Party of China in late 2012, which introduced the "innovation-driven development strategy". This strategy identified innovation as the core engine for accelerating the transformation of the growth model and enhancing economic vitality. National Research and Development (R&D) expenditure increased from 300.31 billion RMB in 2006 to 2,795.63 billion RMB in 2021, with an average annual growth rate of 16.58%. Additionally, the number of granted invention patents rose from 57,786 in 2006 to 695,946 in 2021, achieving an average annual growth rate of 18.38%.

In 2021, national real estate development investment accounted for 11.86% of China's Gross Domestic Product (GDP), while national R&D investment expenditure accounted for 2.43% of GDP. This highlights the importance of exploring the relationship between these two critical activities in China's economy at the micro level. Although the "innovation-driven development strategy" was introduced in 2012 and the government has implemented various policies to encourage firms to engage in innovative activities, the proportion of R&D investment expenditure to GDP increased by only 1.06 percentage points from 2006 to 2021. In contrast, the proportion of real estate development investment to GDP increased by 3.01 percentage points over the same period. This disparity suggests that, despite government guidance and support, China's economic transformation from a factor-driven to an innovation-driven model faces significant challenges. Understanding the sources and mechanisms of these challenges is crucial for facilitating the smooth and rapid transformation of China's economy. The macroeconomic data mentioned above are sourced from the Wind Database.

3.1.2. Measurement of firm innovation investment

To investigate these issues, we draw on a sample from China's A-share listed companies for the period 2011 to 2021[3]. The firm-level data are obtained from the Wind Database, which provides extensive information on each firm's basic characteristics, accounting data, and governance structures. We use R&D expenditures to capture firm innovation investment; however, the raw dataset contains many missing values for R&D inputs, necessitating careful treatment.

In the existing literature, missing R&D expenditures are commonly treated as zero (Hirshleifer et al., 2013; Fang et al., 2014; Custódio et al., 2019). This practice can be partially justified in the Chinese context for several reasons. First, China's rapid economic growth, historically driven by factor inputs, has led some firms to place relatively little emphasis on R&D, resulting in blank reported R&D spending. Second, since the 18th National Congress of the Communist Party of China in 2012, numerous innovation incentive policies – such as tax reductions and R&D subsidies – have been introduced. As a result, listed companies that do invest in innovation have strong incentives to disclose R&D expenditures to benefit from these policies. Third, in the absence of mandatory disclosure requirements, firms that voluntarily report their R&D spending are typically those prioritizing innovation, meaning that ignoring missing values could cause significant sample selection bias.

However, prior research also notes that firms sometimes report missing R&D expenditures while simultaneously disclosing patent applications or authorizations (Jia, 2019; Chen et al., 2022a). Simply classifying all missing R&D expenditures as zero can therefore introduce measurement error (Brown et al., 2013). Some firms may strategically withhold disclosure of R&D spending to safeguard their research directions from competitors or to mitigate negative market reactions tied to short-term profitability concerns.

Patents, by contrast, serve as formal protection for firms' innovation outcomes and are unlikely to be deliberately concealed. Indeed, patent applications and authorizations are widely recognized as indicators of firms' innovation investment intensity (Hall et al., 2005; Koh & Reeb, 2015). Accordingly, we use patent information to cross-check missing R&D expenditures. Because it typically takes 12 to 36 months from patent application to authorization, we assume that patent applications more accurately reflect the timing of R&D expenditures. Consequently, if a firm discloses no patent applications in a given year, we replace its missing R&D expenditures with zero. We further validate this approach in subsequent robustness checks.

3.1.3. Measurement of housing price appreciation

We use the city's growth rate of the average price of newly constructed residential properties as a proxy for housing price appreciation for two main reasons. First, city-level housing prices more accurately reflect the specific market environments in which firms operate. Second, because China's urban land supply and real estate development are controlled by local governments, local firms are more likely to participate in the local real estate market than non-local firms due to their close relationships with local governments (Rong et al., 2016). This indicates that China's real estate market is relatively segmented, as housing price changes vary significantly across cities, and changes in one city have minimal influence on the investment behaviors of firms in other cities. City housing price data are sourced from the Wind Database, which regularly publishes housing price data for 100 cities. However, during the examination period, 6 cities were replaced by new ones. To ensure data continuity, we restrict the sample to 94 major cities. Additionally, to capture broader city characteristics, we collect other city-level variables from the China Stock Market & Accounting Research (CSMAR) Database, including city fiscal expenditure, population size, industrial development conditions, consumer market size, and the economic pressure of housing prices. Table 1 provides an overview of the definitions and data sources for all variables used in this study.

Table 1. Variable definition and source

Variables	Definitions and data sources
Firm characteristics:	
RDratio	The ratio of the firm's R&D expenditures to total assets (%). Source: Wind Database.
Margin	The firm's main business profit margin, measured as the ratio of main business profit to main business revenue. Source: Wind Database.
Size	The firm's size, measured as the natural logarithm of total assets. Source: Wind Database.
Lev	The firm's financial leverage, measured as the ratio of total liabilities to total assets. Source: Wind Database.
Age	The firm's age, measured as the natural logarithm of 1 plus the firm's duration. Source: Wind Database.
Fixratio	The firm's fixed asset ratio, measured as the ratio of fixed assets to total assets. Source: Wind Database.
Top10	The shareholding ratio of the firm's top 10 shareholders. Source: Wind Database.
Indep	The independence of the firm's board, measured as the ratio of independent directors to board size. Source: Wind Database.
Wedge	The wedge between the rates of return on housing investment and innovation investment, measured as the difference between the growth rate of housing prices in the city where the firm is located and the firm's main business profit margin. Source: Wind Database.
Output	The firm's output scale, measured as the natural logarithm of operating revenues. Source: Wind Database.
SOE	A dummy variable that equals 1 if the firm is state-owned, and 0 otherwise. Source: Wind Database.
Patent	The number of the firm's independently granted patents in the current year. Source: CSMAR Database.
City characteristics:	
House	The annual growth rate of the average price of newly constructed residential properties in the city. Source: Wind Database.
Cfisexp	The city's fiscal expenditure, measured as the natural logarithm of the city's budgetary fiscal expenditure. Source: CSMAR Database.
Cpop	The city's population size, measured as the natural logarithm of the city's total population. Source: CSMAR Database.
Cinfirm	The number of above-designated-size industrial firms in the city, measured as the natural logarithm of the number of industrial firms with an annual main business revenue of 20 million RMB or more in the city. Source: CSMAR Database.
Cconsum	The city's consumer market size, measured as the natural logarithm of the city's total retail sales of consumer goods. Source: CSMAR Database.
Chpgdp	The pressure of city housing price on economy, measured as the ratio of the city's house price to per capita GDP. Source: Wind Database and CSMAR Database.
Macro financial characteristics:	
RR7d	The 7-day reverse repo rate (%). Source: Wind Database.
LPR1yr	The 1-year loan prime rate (%). Source: Wind Database.

Note: This table presents the definitions and data sources of relevant variables.

3.1.4. A brief description of the sample

We clean the raw data using the following procedure: (i) exclude observations from the financial, insurance, and real estate industries; (ii) exclude observations with missing firm accounting information and city-related information; (iii) exclude observations violating the General Accounting Principles[3]; (iv) exclude observations with negative firm age; (v) exclude observations with Special Treatment (ST) or Particular Transfer (PT) status. After this data filtering process, the final sample consists of 15,954 observations from 2,759 firms spanning the years 2011 to 2021. To mitigate the influence of outliers, all firm-level continuous variables are winsorized at the 1% level in both tails. Table 2 presents descriptive statistics for the variables included in our analysis. On average, the R&D ratio is 1.369%, indicating that R&D expenditures comprise around 1.369% of total assets during the sample period.

Table 2. Summary statistics

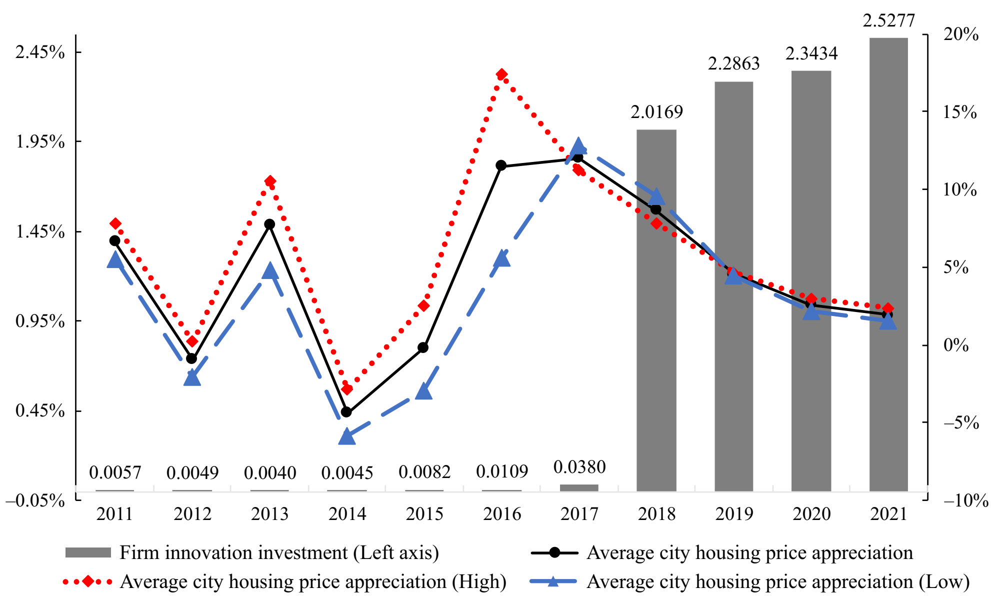
Panel A. Firm characteristics						
Variables	N	Mean	St. Dev.	Min	Median	Max
RDratio	15,954	1.369	2.087	0.000	0.210	17.291
Margin	15,866	0.272	0.174	–0.017	0.239	0.837
Size	15,954	13.121	1.273	9.069	12.952	16.638
Lev	15,954	0.430	0.198	0.055	0.426	0.882
Age	15,954	2.987	0.289	1.386	2.996	3.584
Fixratio	15,954	0.207	0.158	0.004	0.171	0.689
Top10	15,928	0.577	0.150	0.238	0.582	1.000
Indep	15,954	0.377	0.056	0.182	0.364	0.800
Wedge	15,849	–0.226	0.192	–0.814	–0.202	0.215
Output	15,954	12.461	1.464	8.506	12.311	16.138
SOE	15,954	0.374	0.484	0.000	0.000	1.000
Patent	15,954	52.352	201.721	0.000	11.000	6,741.000
Panel B. City characteristics						
Variables	Years	Mean	St. Dev.	Min	Median	Max
House	2011–2021	0.046	0.084	–0.420	0.030	0.503
Cfisexp	2011–2021	15.550	0.782	13.481	15.443	18.250
Cpop	2011–2021	6.255	0.624	4.047	6.366	8.136
Cinfirm	2011–2021	7.491	1.007	3.045	7.620	9.475
Cconsum	2011–2021	16.619	0.836	13.665	16.556	19.013
Chpgdp	2011–2021	0.123	0.060	0.027	0.110	0.529
Panel C. Macro financial characteristics						
Variables	Years	Mean	St. Dev.	Min	Median	Max
RR7d	2012–2021	2.818	0.700	2.200	2.543	4.100
LPR1yr	2013–2021	4.592	0.710	3.846	4.306	5.731

Note: This table presents the summary statistics of firm, city and macro financial characteristics, including the mean, standard deviation, minimum, median and maximum.

[3] This situation includes: (i) total assets, total liabilities, equity, liquid liabilities, non-liquid liabilities or operating revenues are negative; (ii) total assets are less than total liabilities, equity, fixed assets, liquid assets or non-liquid assets.

This measure exhibits substantial variation, with a maximum of 17.291% and a minimum of 0. In terms of housing price appreciation, the average annual growth rate for sample cities is 4.6% over the examination period, although this rate varies considerably across cities – from a high of 50.3% to a low of –42.0%.

To illustrate the relationship between housing price changes and firm innovation investment, Figure 4 shows both the average growth rate of city housing prices and the average firm innovation investment. From the bar chart, we see that the average innovation investment – measured as the ratio of R&D expenditures to total assets (%) – displays a clear phased trend. Prior to 2017, the average investment level was very low, never exceeding 0.05%. However, it spiked to 2.0169% in 2018 and continued rising thereafter. This notable increase in 2018 stems primarily from two factors. First, the onset of the China – U.S. trade dispute that year prompted Chinese firms to strengthen their independent R&D capabilities. Second, the Chinese government expanded the 75% tax deduction policy for R&D expenditures beyond technology-based SMEs to almost all enterprises (except those on the "negative list"), markedly boosting innovation incentives. As a result, firms were motivated to enhance R&D efforts and disclose – or even inflate – their reported R&D expenditures.



Note: This figure illustrates the average growth rate of city housing prices and the average firm innovation investment in China from 2011 to 2021. The bar chart represents the average innovation investment of sample firms in each year, measured as the ratio of firm R&D expenditures to total assets (%). The black solid line depicts the average growth rate of housing prices across the 94 cities in each year. The red dotted line shows the average growth rate of housing prices in cities with an annual average growth rate above the median over the examination period, while the blue dashed line represents the average growth rate of housing prices in cities with an annual average growth rate below the median over the same period.

Figure 4. Trend of city housing price appreciation and firm innovation investment in China

Regarding housing price appreciation, we divide the 94 cities into two groups – fast growth and slow growth – based on their annual average growth rate of housing prices over the examination period. We then calculate the average growth rate of housing prices for the fast growth group, the slow growth group, and the entire sample in each year, represented by the red dotted line, the blue dashed line, and the black solid line in Figure 4, respectively. Housing price appreciation in these three groups follows a similar pattern, suggesting that housing price changes across all cities were largely driven by a common factor during the examination period, namely regulatory policies targeting the real estate market.

Before 2017, the relationship between housing price appreciation and firm innovation investment showed mixed trends, moving in the same direction at times and in opposite directions at others. This reflects the coexistence of the "collateral effect" and the "crowding-out effect" of the booming real estate market on firm innovation, with each effect alternating as the dominant force. However, since 2018, housing price appreciation and firm innovation investment have exhibited a clear negative relationship: while the growth rate of housing prices declined, firm innovation investment increased. This suggests that during this period, the "crowding-out effect" became the dominant force. Overall, the insights from Figure 4 are not straightforward, and further formal analysis is required.

3.2. Empirical strategy

3.2.1. Test of Proposition 1

To verify the crowding-out effect of housing price appreciation on firm innovation investment, we construct the following baseline regression Equation:

$$RDratio_{i,c,t} = \beta_0 + \beta_1 House_{c,t-1} + \beta_2 X_{i,c,t-1} + \beta_3 Z_{c,t-1} + \eta_i + \lambda_t + \varepsilon_{i,c,t}, \tag{18}$$

where i, c and t denote the firm, city and year, respectively. The dependent variable $RDratio_{i,c,t}$ represents the innovation investment of firm i located in city c in year t. Firms of different sizes require varying levels of investment to achieve successful innovation due to differences in their capital and labor inputs (Yuan et al., 2022). To account for this, we measure a firm's innovation investment using the ratio of its R&D expenditures to total assets, thereby excluding the influence of firm size. The key independent variable $House_{c,t-1}$ denotes the housing price appreciation of city c in year $t-1$. In line with the model definition, we measure a city's housing price appreciation using the annual growth rate of the average price of newly constructed residential properties. To account for the time lag in firms' responses to housing price changes and to mitigate potential endogeneity caused by reverse causality, we lag the key independent variable by one period.

$X_{i,c,t-1}$ is a vector of firm-level control variables that may influence firm innovation investment. As implied by our theoretical model, since the return on innovation investment is realized through improvements in a firm's productivity and, consequently, its main business revenues, a higher main business profit margin may encourage increased innovation investment. Therefore, we control for the firm's main business profit margin *Margin*, measured as the ratio of main business profit to main business revenue. Referring to prior studies on firm innovation investment (Rong et al., 2016; Yuan et al., 2022), we include firm size, financial leverage, age, and fixed asset ratio as control variables. Consistent with the literature, firm size (*Size*) is measured as the natural logarithm of total assets. Firm financial leverage (*Lev*) is measured as the ratio of total liabilities to total assets. Firm age (*Age*) is measured as the natural logarithm of 1 plus the firm's duration. The fixed asset ratio (*Fixratio*) is measured as the ratio of the firm's fixed assets to total assets. In addition, related literature suggests that firm governance structures influence its innovation activities. For instance, Jiang et al. (2020) show that large shareholders significantly affect firm innovation investment. To account for this, we control for the shareholding ratio of the top 10 shareholders (*Top10*). Furthermore, following Balsmeier et al. (2017) and Yuan et al. (2022), we control for firm board independence (*Indep*), measured as the ratio of independent directors to total board size.

A firm's innovation investment may also be influenced by the characteristics of the city in which it is located. Therefore, we include a vector of city-level control variables $Z_{c,t-1}$. Since local government support and subsidies for R&D activities can encourage firm innovation investment, we control for city fiscal expenditure (*Cfisexp*), measured as the natural logarithm of the city's budgetary fiscal expenditure. Chen et al. (2022b) suggest that a large city population contributes to R&D activities through knowledge spillovers. Accordingly, we control for city population size (*Cpop*), measured as the natural logarithm of the city's total population. To account for the agglomeration effects of industrial firms, we include the natural logarithm of the number of above-designated-size industrial firms in the city (*Cinfirm*). As the city's market size and spending power influence the expected returns and motivations for firm innovation, we control for city consumer market size (*Cconsum*), measured as the natural logarithm of the city's total retail sales of consumer goods. Additionally, we use the ratio of city house price to per capita GDP (*Chpgdp*) to measure the pressure of housing prices on city economic development. A higher value of this ratio indicates that the real estate market may crowd out more resources from other economic sectors, thereby affecting firms' ability to acquire innovative resources. To mitigate potential endogeneity caused by reverse causality, all firm-level and city-level control variables are lagged by one period.

Firm fixed effects (η_i) capture the influence of time-invariant, unobservable firm characteristics, while year fixed effects (λ_t) account for business cycle fluctuations. The term $\varepsilon_{i,c,t}$ is the error term. Because the variable of interest ($House_{c,t-1}$) is defined at the city-year level, robust standard errors clustered at the city-year level are employed. According to **Proposition 1**, we expect the corresponding coefficient β_1 to be significantly negative.

3.2.2. Test of Proposition 2

To explore the impact of firm debt repayment capabilities on the relationship between housing price appreciation and firm innovation investment, we use a split-sample regression approach. As previously analyzed, firms with larger output scales or state-owned ownership are considered to have superior debt repayment capabilities. Accordingly, we use two proxy variables to represent the firm's debt repayment capabilities. The first proxy is the firm's output scale (*Output*), measured as the natural logarithm of operating revenues. The second proxy is the firm's ownership status (*SOE*), which is a dummy variable equal to 1 if the firm is state-owned and 0 otherwise. Other specifications, including control variables and fixed effects, are consistent with those in regression Eq. (18).

Specifically, we divide the sample into two groups based on whether a firm's output scale is above the median value of the sample, categorizing them as the low output group and the high output group. We then re-estimate regression equation (1) for both subsamples and compare the coefficients of $House_{c,t-1}$. According to **Proposition 2**, we expect the coefficient of $House_{c,t-1}$ estimated from the low output subsample to be significantly negative, while the coefficient from the high output subsample is expected to be insignificant or less significantly negative. Similarly, for firm ownership status, we divide the sample into state-owned and non-state-owned groups and repeat the estimation of regression Eq. (18) for both subsamples. We anticipate the coefficient of $House_{c,t-1}$ to be significantly negative in the non-state-owned group, whereas in the state-owned group, it is expected to be insignificant or less significantly negative.

3.2.3. Test of Proposition 3

We use the split-sample regression method to examine the influence of firm R&D capabilities on the relationship between housing price appreciation and firm innovation investment. Existing literature typically uses patent applications as a proxy for firm R&D capabilities (Tan & Zhu, 2024; Zhou et al., 2024). However, compared with patent applications, the authorization of patents can better reflect a firm's actual innovation progress. Moreover, since innovative activity is a long-term process, patent applications in a given year may inadequately represent a firm's R&D capabilities. Considering these factors, we use the number of independently granted patents in the current year $Patent_{i,c,t}$ to measure the firm's yearly actual innovation progress. We then measure the firm's R&D capabilities by calculating the number of its accumulated independently granted patents during the examination period $\sum_t Patent_{i,c,t}$.

To verify **Proposition 3**, we divide the sample into two groups based on whether the number of accumulated independently granted patents $\sum_t Patent_{i,c,t}$ is above the median value of the sample, categorizing them as the low R&D capability group and the high R&D capability group. We then re-estimate regression Eq. (18) for both subsamples. We expect the coefficient of $House_{c,t-1}$ estimated from the low R&D capability subsample to be significantly negative, while the coefficient from the high R&D capability subsample is expected to be insignificant or less significantly negative.

3.2.4. Test of Proposition 4

To explore how the credit environment affects the crowding-out effect of housing price appreciation on firm innovation investment, we construct the following regression Equation:

$$RDratio_{i,c,t} = m_0 + m_1 House_{c,t-1} + m_2 Prate_{t-1} + m_3 House_{c,t-1} \times Prate_{t-1} + m_4 X_{i,c,t-1} + m_5 Z_{c,t-1} + \eta_i + \varepsilon_{i,c,t}, \quad (19)$$

where $Prate_{t-1}$ denotes the policy interest rate, with a higher value indicating a tighter credit environment. The 7-day reverse repo rate, $RR7d$, is one of the core short-term policy interest rates in China's monetary policy framework and has been regularly employed in the central bank's Open Market Operations (OMO) since 2012. We therefore use it as a proxy for China's policy interest rate, as it effectively reflects monetary policy's impact on short-term funding costs in the interbank market. Additionally, we employ the 1-year Loan Prime Rate

(LPR), $LPR1yr$, as another proxy for China's policy interest rate, which has been available since 2013 and influences the costs of long-term funds such as bank loans. Other specifications are the same as those in regression Eq. (18), with the only exception being that we do not include year fixed effects. This is because policy interest rates are time series variables that vary only over time and would be omitted from the estimation if year fixed effects were included. In addition, we use the centered housing price appreciation ($House_{c,t-1}$) and policy interest rate ($Prate_{t-1}$) in the estimation to enhance the interpretability of coefficients m_1 and m_2. According to **Proposition 4**, we expect the coefficient of the interaction term (m_3) to be significantly positive.

4. Empirical results

4.1. Baseline results

Table 3 shows the empirical findings for testing **Proposition 1**. Column (1) presents the estimation results without control variables. Column (2) incorporates firm-level control variables, and Column (3) adds city-level control variables. Across all columns, the coefficients of $House_{c,t-1}$ are negative and statistically significant at the 5% level, indicating that housing price appreciation exerts a robust crowding-out effect on firm innovation investment. Furthermore, the adjusted R^2 values increase from Column (1) to Column (3), suggesting that adding firm-level and city-level controls enhances the explanatory power of regression Eq. (18).

According to Column (3), the coefficient of $House_{c,t-1}$ is –0.191, implying that a 10% rise in city housing prices is associated with a 0.0191 percentage point reduction in a firm's innovation investment – equivalent to around 1.40% (0.0191/1.369) of the average innovation investment level among sample firms reported in Table 2. These findings underscore that the crowding-out effect is both statistically significant and economically meaningful, lending strong support to **Proposition 1**.

These findings are consistent with Rong et al. (2016), who report that rising housing prices encourage industrial firms to divert resources away from innovative activities. However, Rong et al. (2016) document a smaller crowding-out effect compared to this study[4]. The larger effect size observed in our analysis may be attributed to differences in sample selection. First, we use a more recent sample period (2011–2021), whereas Rong et al. (2016) focus on the period from 1999 to 2007. Since housing prices in China surged rapidly after the 2008 Global Financial Crisis, driven by the implementation of large-scale economic stimulus plans, the motivation for firms to invest in real estate may have been stronger during our sample period. Second, while Rong et al. (2016) restrict their sample to 35 major cities, primarily first-tier cities or provincial capitals, our sample includes nearly 100 cities, encompassing many non-first-tier and non-capital cities where firms face greater developmental constraints. Firms in these cities are more likely to engage in real estate speculation, further amplifying the crowding-out effect.

[4] The empirical results in Rong et al. (2016) indicate a 10% increase in city housing prices leads to a 0.0021 percentage point decrease in firm R&D ratio.

Table 3. Baseline results: test of Proposition 1

	(1)	(2)	(3)
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$House_{c,t-1}$	–0.186**	–0.200**	–0.191**
	(0.086)	(0.089)	(0.082)
$Margin_{i,c,t-1}$		0.849***	0.894***
		(0.153)	(0.166)
$Size_{i,c,t-1}$		0.223***	0.227***
		(0.025)	(0.027)
$Lev_{i,c,t-1}$		0.616***	0.597***
		(0.104)	(0.109)
$Age_{i,c,t-1}$		0.404**	0.562**
		(0.195)	(0.236)
$Fixratio_{i,c,t-1}$		0.236	0.248
		(0.155)	(0.165)
$Top10_{i,c,t-1}$		–2.472***	–2.546***
		(0.178)	(0.189)
$Indep_{i,c,t-1}$		–0.740***	–0.868***
		(0.248)	(0.260)
$Cfisexp_{c,t-1}$			0.315***
			(0.113)
$Cpop_{c,t-1}$			0.534**
			(0.234)
$Cinfirm_{c,t-1}$			–0.237**
			(0.101)
$Cconsum_{c,t-1}$			–0.089
			(0.101)
$Chpgdp_{c,t-1}$			–0.926
			(0.873)
Constant	1.345***	–1.539**	–7.018***
	(0.013)	(0.663)	(2.051)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	15,757	15,608	14,497
$Adj-R^2$	0.730	0.746	0.748

Note: This table estimates the effects of housing price appreciation on firm innovation investment. Column (1) presents the results without control variables. Column (2) adds firm-level control variables based on Column (1). Column (3) incorporates both firm-level and city-level control variables. Robust standard errors clustered at the city-year level are reported in the parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

Regarding firm-level control variables, the coefficient of $Margin_{i,c,t-1}$ is significantly positive, indicating that firms with strong performance in their core business are more likely to increase innovation investment to enhance their competitive advantages. Similarly, the coefficient of $Size_{i,c,t-1}$ is also significantly positive, consistent with previous studies (Rong et al., 2016; Tan & Zhu, 2024), which suggest that larger firms have more resources to allocate toward innovative activities. The significantly positive coefficient of $Lev_{i,c,t-1}$ suggests that higher financial leverage may reflect strong external financing capabilities, thereby facilitating firm innovation investment. Additionally, the coefficient of $Age_{i,c,t-1}$ is significantly positive, implying that older firms may pursue innovation as a strategy to extend their lifecycle. In contrast, the significantly negative coefficient of $Top10_{i,c,t-1}$ suggests that large shareholders may prioritize short-term, low-risk projects over innovative activities to serve their personal interests. Finally, the significantly negative coefficient of $Indep_{i,c,t-1}$ indicates that higher board independence may not be conducive to innovation investment. This could be because independent directors, due to their limited involvement in daily operations and insufficient understanding of firm innovation processes, tend to adopt more conservative decision-making approaches.

With respect to city-level control variables, the coefficient of $Cfisexp_{c,t-1}$ is significantly positive, supporting our expectation that greater fiscal expenditure at the city level contributes to firm innovation investment. The significantly positive coefficient of $Cpop_{c,t-1}$ aligns with the findings of Chen et al. (2022b), which suggest that a larger population fosters firm innovation investment through knowledge spillovers. Lastly, the coefficient of $Cinfirm$ is significantly negative, suggesting that in cities where large industrial firms are highly concentrated, firms tend to reduce innovation investment. This decline may arise from weakened positive externalities of innovation and the crowding effects caused by agglomeration.

4.2. Endogeneity test

In the baseline regression, we address the endogeneity problem arising from reverse causality by using the lagged term of city housing price appreciation as our key independent variable. Additionally, we include firm and year fixed effects to mitigate endogeneity concerns caused by omitted variables. However, the risk of reverse causality may still persist. For instance, a decline in firm innovation investment could potentially push up local housing prices via two mechanisms. First, when firms reduce R&D expenditures, they might redirect unused capital to real estate, seeking higher short-term returns, which in turn drives up local housing prices. Second, a prolonged reduction in innovation investment undermines a firm's industry competitiveness, hampering local economic development. Weaker economic growth may lead local governments to spur the housing market, further exacerbating the reverse causality issue. To address these concerns, we employ an Instrumental Variable (IV) approach.

Previous studies have used the interaction term of city housing supply elasticity and the long-term interest rate as an IV for city housing price appreciation (Mian & Sufi, 2011; Chaney et al., 2012; Rong et al., 2016). In cities with inelastic housing supply, housing prices tend to increase rather than expand the housing supply in response to rising real estate demand. The long-term interest rate, on the other hand, captures demand in the national real estate market, with lower rates encouraging greater real estate demand.

Building on this framework, we construct a new IV for housing price appreciation. Following Saiz (2010), which underscore the role of geographic constraints in determining urban housing supply elasticity, we use the extreme range of a city's terrain slope[5] as an indicator of its developable area. Larger terrain slope ranges imply more severe geographic constraints, resulting in faster housing price appreciation when demand rises. Because China is still undergoing interest rate liberalization and exhibits significant regional differences in financial development, we measure city-level demand using the city's per capita loan-deposit gap rather than national long-term interest rates. A higher per capita loan-deposit gap typically reflects stronger local demand, including demand for real estate.

We then construct our IV ($IV_{c,t}$) by interacting the extreme range of terrain slope with the previous year's per capita loan-deposit gap. This interaction is expected to have a positive relationship with housing price appreciation. Moreover, because the terrain slope is a time-invariant geographic factor, and the prior year's loan-deposit gap should not be affected by a firm's current innovation investment, this interaction term meets the exogeneity requirement for an instrumental variable.

We re-estimate Eq. (18) using the Two-Stage Least Squares (2SLS) approach, employing the interaction term between the extreme range of city terrain slope and the previous year's per capita loan-deposit gap as the IV ($IV_{c,t}$) for city housing price appreciation ($House_{c,t}$). Table 4 presents the IV estimation results. In Column (1), the first-stage regression shows a positive coefficient on the IV that is significant at the 1% level, aligning with our expectations. Column (2) reports the second-stage regression results, where the coefficient on city housing price appreciation remains significantly negative at the 5% level. Furthermore, the under-identification test yields a p-value below 0.01, indicating no under-identification issues, and the Cragg-Donald Wald F statistic exceeds the critical value of 10, ruling out concerns about a weak IV. Overall, the results in Table 4 confirm that the crowding-out effect of housing price appreciation on firm innovation investment persists even after addressing potential endogeneity concerns.

A comparison between the estimates in Column (3) of Tables 3–4 reveals that the IV estimate for the coefficient of $House_{c,t-1}$ is approximately 8.33 times larger than the baseline regression estimate. This result aligns with our expectations and echoes Jiang (2017), which notes that around 80% of studies published in the "Big Three" finance journals find IV estimates to be, on average, nine times the magnitude of their non-IV counterparts.

As discussed, reverse causality is the primary source of endogeneity in our regressions: a firm's reduced innovation investment can drive housing prices upward through two channels – (1) resource reallocation and (2) local government intervention aimed at boosting the housing market. These mechanisms can lead to conservative baseline estimates, but by employing the IV approach, we more accurately identify causal effects, producing upwardly adjusted regression results. The larger IV estimate in Table 4 corroborates the appropriateness of our chosen IV and suggests that the baseline regressions underestimate the negative impact of housing price appreciation on firm innovation investment. Consequently, these findings highlight the necessity of managing housing price growth to foster firm-level innovation.

[5] The geographic data were obtained from the ASTER Global Digital Elevation Model V003 (Earthdata Search, n.d.) and subsequently processed using ArcGIS software.

Table 4. Endogeneity test: IV estimation

	(1) First-stage	(2) Second-stage
Variables	$House_{c,t}$	$RDratio_{i,c,t}$
$IV_{c,t}$	0.0001*** (0.000)	
$House_{c,t-1}$		−1.591** (0.647)
Firm Controls	YES	YES
City Controls	YES	YES
Under – identification Test	—	0.002
Weak – identification Test	—	540.684
Firm FE	YES	YES
Year FE	YES	YES
Observations	12,916	12,916

Note: This table presents the results of the instrumental variable (IV) estimation, which re-estimates regression equation (1) using the interaction term between the extreme range of city terrain slope and the previous year's per capita loan-deposit gap within the city as the instrumental variable for $House_{c,t-1}$. Column (1) reports the results of the first-stage regression, while Column (2) reports the results of the second-stage regression. The under-identification test provides the *p*-value, and the weak-identification test reports the Cragg-Donald Wald F statistic. Robust standard errors clustered at the city-year level are reported in parentheses. Coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3. Robustness checks

To further validate the conclusions drawn from the baseline regressions, we perform several robustness checks in this Subsection.

4.3.1. The mechanism of the crowding-out effect

As analyzed in Section 2, greater housing price appreciation makes housing investment more profitable for firms, thereby increasing the opportunity cost of innovation investment and squeezing out resources for innovative activities. Based on this reasoning, we infer that the difference between the rates of return on housing investment and innovation investment is a key mechanism underlying the crowding-out effect of housing price appreciation on firm innovation investment.

To test this mechanism, we construct an indicator to measure the difference between the two rates of return ($Wedge_{i,c,t}$). Since the return on firm innovation investment is realized through productivity growth and, consequently, main business revenues, we use the firm's main business profit margin as a proxy for the return on innovation investment. $Wedge_{i,c,t}$ is calculated as the difference between city housing price appreciation ($House_{c,t}$) and the firm's main business profit margin ($Margin_{i,c,t}$). We then re-estimate regression equation (1), replacing $House_{c,t-1}$ with $Wedge_{i,c,t-1}$. Column (1) of Table 5 presents the results, where the coefficient of $Wedge_{i,c,t-1}$ is significantly negative at the 1% level. This finding indicates that the difference between the rates of return on housing investment and innovation investment serves as an important mechanism driving the crowding-out effect of housing price appreciation on firm innovation investment.

4.3.2. Excluding negative net profit sample

Firms with negative net profits may face severe financial constraints, leading to investment behaviors that differ significantly from those of more financially stable firms. In contrast, firms with positive net profits typically have stable cash flows and operate under normal conditions, allowing their innovation investment decisions to better reflect the impact of the market environment rather than irrational behaviors driven by survival pressures.

To ensure the robustness of our baseline results, we exclude observations with negative net profits and re-estimate regression Eq. (18) using a subsample of firms with positive net profits. The results, presented in Column (2) of Table 5, indicate that the coefficient of $House_{c,t-1}$ remains negative and statistically significant, with a magnitude similar to that in the baseline regressions. This finding confirms that the crowding-out effect of housing price appreciation on firm innovation investment persists even after excluding firms with negative net profits.

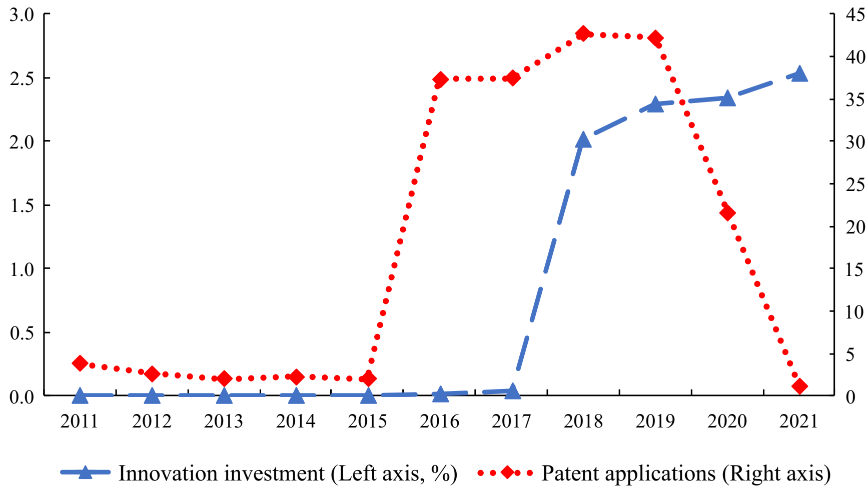
Table 5. Additional robustness checks

	(1)	(2)	(3)
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$Wedge_{i,c,t-1}$	–0.733*** (0.149)		
$House_{c,t-1}$		–0.180** (0.083)	–0.299*** (0.100)
Constant Term	YES	YES	YES
Firm Controls	YES	YES	YES
City Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	14,497	12,777	16,560
$Adj-R^2$	0.748	0.755	0.685

Note: This table presents several robustness checks to verify the baseline results. Column (1) re-estimates regression equation (1), replacing $House_{c,t-1}$ with the difference between the growth rate of city housing prices and the firm's main business profit margin $Wedge_{i,c,t-1}$. Column (2) presents the estimation results of regression equation (1) using the subsample of firms with positive net profits. Column (3) reports the estimation results of regression equation (1), where missing firm innovation investment for 2006 and 2007 are imputed using data from 2018 onward. Robust standard errors clustered at the city-year level are reported in parentheses. Coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.3. Accounting for firms concealing R&D expenditures

As discussed in Section 3.1.1, we set missing R&D expenditures to zero for observations that had no patent applications in a given year. However, this approach may not capture the potential impact of housing price appreciation on firms that report no formal R&D spending but still apply for patents. To explore this, we compare annual averages of both innovation investment and patent applications among China's A-share listed companies (see Figure 5). The comparison shows a notable discrepancy for 2016 and 2017: while the number of patent applications surged in 2016 and stayed high in 2017, innovation investment rose slowly during this interval and then spiked in 2018 – after the sharp increase in innovation outputs. One plausible explanation is that many firms were actively innovating but opted to strategically conceal their R&D expenditures.



Note: This figure illustrates the trend of annual averages of innovation investment and patent applications among China's A-share listed companies from 2011 to 2021. The blue dashed line represents the annual average of firms' innovation investment ($RDratio_{i,c,t}$) for each year, while the red dotted line represents the annual average of firm patent applications for each year.

Figure 5. Annual averages of innovation investment and patent applications for China's A-share listed companies (2011–2021)

To address the measurement error in firm innovation investment ($RDratio_{i,c,t}$) and minimize estimation bias in the baseline regressions, we propose a method to impute missing values. Given that patent applications grew steadily from 2016 to 2017[6] – matching the upward trend in firm innovation investment from 2018 onward – we use firm-level data from 2018 onward to predict missing values of $RDratio_{i,c,t}$ for 2016 and 2017, based on the following regression Equation:

[6] The rapid decline in firms' patent applications since 2020 may be attributed to the following key factors: First, the Chinese government has tightened the examination standards for patents since 2019, making it more difficult for low-quality or repetitive patents to gain approval. Second, disputes between China and the U.S., along with the outbreak of the COVID-19 pandemic, have constrained international cooperation and imports in high-tech fields. These factors are likely to push firms to allocate more resources to innovation projects and extend the time required for their innovation efforts to translate into patents, ultimately leading to a reduction in the number of patent applications.

$$RDratio_{i,t} = \beta_0 + \beta_1 M_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t}, \quad (20)$$

where $M_{i,t-1}$ denotes firm-level variables consistent with those in regression Eq. (18) (i.e., $X_{i,c,t-1}$), η_i and λ_t denote firm fixed effects and year fixed effects respectively, and $\nu_{i,t}$ is the error term clustered at the firm-level.

Next, for observations with non-missing innovation investment data, we calculate the residual between the true innovation investment and the value predicted by regression Eq. (20), and then exclude observations where the absolute value of the residual exceeds three times the standard deviation of the residuals to mitigate the impact of outliers.

We then re-estimate Eq. (18) using the processed data, and the results are shown in Column (3) of Table 5. The coefficient of $House_{c,t-1}$ remains significantly negative at the 1% level, with both a larger magnitude and greater statistical significance compared to the baseline regressions. This outcome indicates that after accounting for the potential effects of housing price appreciation on the innovation investment of firms concealing R&D expenditures, the crowding-out effect endures, further reaffirming the robustness of our baseline conclusions.

4.4. The impact of firm debt repayment capabilities

To analyze how firm debt repayment capabilities influence the crowding-out effect of housing price appreciation on innovation investment, we adopt a split-sample regression strategy and employ two proxy variables: firm output scale and ownership status. Table 6 shows the corresponding results.

Columns (1) and (2) report the results using firm output scale as the proxy for debt repayment capabilities. In the low-output group, the coefficient of $House_{c,t-1}$ is significantly negative, whereas in the high-output group, it is positive but not statistically significant. This finding implies that firms with larger output scales are better able to mitigate the adverse effects of housing price appreciation on innovation investment, aligning with our initial expectation. Additionally, a Fisher's permutation test yields a p-value of 0.016, confirming that the coefficient difference between the two groups is statistically significant.

These findings are intuitive. Firms with large output scales typically possess more fixed assets and higher market shares, which provide them with abundant and stable cash flows. Consequently, banks perceive these firms as having lower default risks, enabling them to secure cheaper and more accessible bank loans for investment, as highlighted in our theoretical model. The lower cost of bank loans allows these firms to allocate more resources to long-term and high-risk innovation investments, even in the context of rising housing prices.

Columns (3)–(4) of Table 6 report the regression results when firm ownership status is used to represent debt repayment ability. In the non-state-owned group, the coefficient of $House_{c,t-1}$ is significantly negative, whereas in the state-owned group, it is statistically insignificant. Additionally, the Fisher's permutation test reports a p-value of 0.078, suggesting the difference in coefficients between the two groups is statistically significant. These findings imply that State-Owned Enterprises (SOEs) are better able to mitigate the adverse effect of housing price appreciation on their innovation investment.

Table 6. The impact of firm debt repayment capabilities: test of Proposition 2

	Firm output scale		Firm ownership status	
	(1)	(2)	(3)	(4)
Sample	Low output firms	High output firms	SOE	Non-SOE
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$House_{c,t-1}$	–0.431** (0.199)	0.027 (0.054)	0.149 (0.092)	–0.298** (0.133)
Fisher's Permutation Test	0.016		0.078	
Constant Term	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES
City Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	7,089	7,114	5,413	9,021
$Adj-R^2$	0.786	0.772	0.686	0.761

Note: This table estimates the impact of firm debt repayment capabilities on the crowding-out effect of housing price appreciation on firm innovation investment. Columns (1) and (2) re-estimate regression equation (1) using the low output subsample and the high output subsample, respectively, with firm output scale (*Output*) as the proxy for firm debt repayment capabilities. Columns (3) and (4) re-estimate regression equation (1) using the state-owned subsample and the non-state-owned subsample, respectively, with firm ownership status (*SOE*) as the proxy for firm debt repayment capabilities. The Fisher's permutation test reports the *p*-value of the difference in coefficients between the two subsamples after 500 repetitions. Robust standard errors clustered at the city-year level are reported in the parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

The mechanism behind these results is straightforward: in China, banks tend to view SOEs as having low default risk because of implicit government credit support. Consequently, SOEs have greater financing capacity and are less prone to trade-offs in their investment decisions.

Overall, the results in Table 6 support **Proposition 2**, demonstrating that the crowding-out effect of housing price appreciation on firm innovation investment is mitigated in firms with stronger debt repayment capabilities.

4.5. The impact of firm R&D capabilities

In this Subsection, we investigate the impact of firm R&D capabilities on the relationship between housing price appreciation and firm innovation investment. We use the number of accumulated independently granted patents during the examination period as a proxy for firm R&D capabilities. Table 7 presents the results of the split-sample regressions.

In Column (1), the coefficient of $House_{c,t-1}$ in the low R&D capability group is significantly negative at the 1% level. In Column (2), the coefficient for the high R&D capability group is also negative and statistically significant, although its magnitude and statistical significance are lower than those in Column (1). In addition, a Fisher's permutation test confirms that the difference in coefficients between the two groups is statistically significant.

Table 7. The impact of firm R&D capabilities: test of Proposition 3

	(1)	(2)
Sample	Low R&D capability firms	High R&D capability firms
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$House_{c,t-1}$	–0.464*** (0.152)	–0.130* (0.071)
Fisher's Permutation Test	0.066	
Constant Term	YES	YES
Firm Controls	YES	YES
City Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
Observations	7,131	7,366
$Adj-R^2$	0.763	0.753

Note: This table estimates the impact of firm R&D capabilities on the crowding-out effect of housing price appreciation on firm innovation investment. Columns (1) and (2) re-estimate regression equation (1) using the low R&D capability subsample and the high R&D capability subsample, respectively. The Fisher's permutation test reports the *p-value* for the difference in coefficients between the two subsamples based on 500 repetitions. Robust standard errors clustered at the city-year level are reported in parentheses. Coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

These results suggest that the crowding-out effect of housing price appreciation on firm innovation investment is mitigated in firms with stronger R&D capabilities, thereby supporting **Proposition 3**. This conclusion is intuitive. Firms with better R&D capabilities are able to achieve greater improvements in productivity, which result in higher main business revenues and establish long-term competitive advantages. To sustain these advantages, firms with stronger R&D capabilities are less likely to significantly reduce innovation investment, even in the context of rising housing prices.

4.6. The impact of the credit environment

To assess how the credit environment influences the crowding-out effect of housing price appreciation on firm innovation investment, we estimate regression Eq. (19). Column (1) of Table 8 employs the 7-day reverse repo rate ($RR7d$) as a proxy for the policy interest rate. The coefficient of $House_{c,t-1}$ remains significantly negative, consistent with the baseline results. Similarly, the coefficient of $RR7d_{t-1}$ is significantly negative, suggesting that a tighter credit environment constrains firm innovation investment. Moreover, the coefficient of the interaction term between housing price appreciation and the 7-day reverse repo rate ($House_{c,t-1} \times RR7d_{t-1}$) is significantly positive at the 5% level, in line with the prior prediction.

Column (2) presents analogous findings when employing the 1-year Loan Prime Rate ($LPR1yr$) as the proxy for the policy interest rate. Both coefficients of $House_{c,t-1}$ and $LPR1yr_{t-1}$ remain significantly negative, while the coefficient of their interaction term ($House_{c,t-1} \times LPR1yr_{t-1}$) is significantly positive at the 10% level.

Table 8. The impact of credit environment: Test of Proposition 4

	(1)	(2)
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$House_{c,t-1}$	–0.382** (0.163)	–0.316** (0.143)
$RR7d_{t-1}$	–0.312*** (0.062)	
$House_{c,t-1} \times RR7d_{t-1}$	0.576** (0.272)	
$LPR1yr_{t-1}$		–0.381*** (0.090)
$House_{c,t-1} \times LPR1yr_{t-1}$		0.554* (0.294)
Constant Term	YES	YES
Firm Controls	YES	YES
City Controls	YES	YES
Firm FE	YES	YES
Year FE	NO	NO
Observations	13,509	12,368
$Adj-R^2$	0.736	0.754

Note: This table estimates the impact of the credit environment on the crowding-out effect of housing price appreciation on firm innovation investment. Columns (1) and (2) present the estimation results of regression equation (2) with the policy interest rate proxied by the 7-day reverse repos interest rate *RR7d* , and the 1-year Loan Prime Rate *LPR1yr* , respectively. Robust standard errors clustered at the city-year level are reported in the parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

The results in both columns indicates that regardless of whether short-term or long-term policy interest rates are used, the crowding-out effect of housing price appreciation on firm innovation investment is mitigated in tighter credit environments, represented by higher policy interest rates. These findings support **Proposition 4**.

This conclusion is intuitive. When the credit environment tightens (i.e., policy interest rates increase), market liquidity contracts, leading to reduced real estate demand, slower housing price appreciation, and higher bank loan interest rates. As a result, firms reduce loan applications and housing investment, thereby mitigating the crowding-out effect on innovation investment.

5. Further analysis

5.1. The role of banks in the "housing price appreciation – firm innovation investment" nexus

According to the theoretical model, banks play a crucial role in the relationship between housing price appreciation and firm innovation investment. In the previous analysis, we examined the indirect influence of banks on this relationship by focusing on firms' repayment capabilities and the macro credit environment. However, due to the lack of matched firm-bank loan data, this subsection further explores the direct influence of banks from both firm-level and city-level perspectives.

At the firm level, we use the firm's debt maturity structure as an indicator of bank credit supply, reasoning that a longer debt maturity implies a greater willingness on the banks' part to grant long-term credit. We perform a split-sample analysis by dividing the sample into two groups – short debt maturity and long debt maturity – based on whether a firm's long-term debt ratio is above the sample median. We then re-estimate regression equation (1) for each subsample, with the results shown in Table 9.

As shown in Column (1) of Table 9, the coefficient of $House_{c,t-1}$ estimated using the short debt maturity subsample is significantly negative at the 5% level. Conversely, the coefficient of $House_{c,t-1}$ estimated using the long debt maturity subsample, presented in Column (2), is not statistically negative. Moreover, a Fisher's permutation test confirms that the difference between these two coefficients is statistically significant, suggesting that the crowding-out effect of housing price appreciation on firm innovation investment is more pronounced among firms with shorter debt maturities.

Table 9. The role of banks in the relationship between housing price appreciation and firm innovation investment

	Firm debt maturity structure		Bank service efficiency	
	(1)	(2)	(3)	(4)
Sample	Short debt maturity firms	Long debt maturity firms	Low service efficiency	High service efficiency
Variables	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$	$RDratio_{i,c,t}$
$House_{c,t-1}$	–0.382** (0.152)	–0.072 (0.056)	–0.431** (0.170)	0.063** (0.031)
Fisher's Permutation Test	0.094		0.040	
Constant Term	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES
City Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	6,989	6,968	6,970	7,246
$Adj-R^2$	0.763	0.798	0.738	0.830

Note: This table estimates the role of banks in the relationship between housing price appreciation and firm innovation investment. Columns (1) and (2) re-estimate regression equation (1) using the short debt maturity subsample and the long debt maturity subsample, respectively. Columns (3) and (4) re-estimate regression equation (1) using subsamples with low bank service efficiency and high bank service efficiency, respectively. The Fisher's permutation test reports the *p-value* for the difference in coefficients between the two subsamples based on 500 repetitions. Robust standard errors clustered at the city-year level are reported in parentheses. Coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

This finding is intuitive. Firms with shorter debt maturities primarily receive short-term credit from banks and often aim to avoid cash flow disruptions caused by maturity mismatches. As housing prices rise, these firms are more inclined to allocate resources to short-term, low-risk housing investments, intensifying the crowding-out effect. Conversely, banks that extend long-term credit allow firms to access more stable funding, reduce liquidity pressures, and undertake larger-scale innovation projects – thereby mitigating the crowding-out effect of housing price appreciation on firm innovation investment.

At the city level, we measure bank service efficiency using the natural logarithm of the average loan amount granted per bank branch in each city. A larger average loan amount per branch typically indicates stronger risk management and loan allocation by the city's banks, reflecting higher service efficiency. We split the sample into two groups – low service efficiency and high service efficiency – based on whether the natural logarithm of the average loan amount in a firm's city exceeds the sample median.

Columns (3) and (4) of Table 9 show the re-estimated results of regression equation (1) using these two subsamples. In the low service efficiency group, the coefficient of $House_{c,t-1}$ is significantly negative at the 5% level. In contrast, the same coefficient in the high service efficiency group is significantly positive at the 5% level. A Fisher's permutation test confirms that this difference is highly significant. Thus, housing price appreciation exerts a crowding-out effect in cities with lower bank service efficiency, yet it boosts firm innovation investment in cities where bank service efficiency is higher.

This divergence primarily stems from the differences in banks' risk management capabilities. In cities with low bank service efficiency, banks are more cautious about lending to high-risk, high-return innovation projects due to limited risk management capabilities, and instead channel funds toward low-risk investments, such as housing. As housing prices rise, these low-risk projects become even more appealing, exacerbating the crowding-out of innovation funding. Conversely, in cities with high bank service efficiency, banks possess advanced risk management capabilities, allowing them to better balance loans between housing needs and innovative endeavors. While higher housing prices still create crowding-out pressures, they also raise the collateral value for firms; as a result, firms can obtain cheaper and larger loans. This collateral enhancement effect offsets the crowding-out, ultimately enabling housing price appreciation to support firm innovation investment.

5.2. The impact of housing price appreciation on firm innovation efficiency

In the previous analysis, we used R&D expenditures as a proxy for firm innovation and demonstrated that housing price appreciation exerts a crowding-out effect on firm innovation. However, R&D expenditures reflect only a firm's innovation inputs and does not capture its innovation outcomes. Furthermore, the crowding-out effect of housing price appreciation on innovation investment may lead firms to reduce resource waste, thereby improving innovation efficiency. As a result, relying solely on the number of patents or invention authorizations may fail to comprehensively measure the impact of housing price appreciation on firm innovation outcomes.

To gain a deeper understanding of how firms allocate limited resources for innovation in the context of rising housing prices, we further examine the effect of housing price appreciation on firm innovation efficiency in this Section. To this end, we construct the following regression Equation:

$$IE_{i,c,t} = \upsilon_0 + \upsilon_1 House_{c,t-1} + \upsilon_2 X_{i,c,t-1} + \upsilon_3 Z_{c,t-1} + \eta_i + \lambda_t + \varepsilon_{i,c,t}, \quad (21)$$

where $IE_{i,c,t}$ denotes the innovation efficiency of firm i in year t. Other specifications are consistent with those in regression Eq. (18).

We measure a firm's innovation efficiency ($IE_{i,c,t}$) as the ratio of innovation outcomes to inputs. Consistent with the previous analysis, we use the ratio of the firm's R&D expenditures to total assets ($RDratio_{i,c,t}$) as the proxy for firm innovation inputs. For firm innovation outcomes, we use four proxies: (1) the total number of independently granted patents ($Patent_{i,c,t}$) in the current year, (2) the number of design patents ($Design_{i,c,t}$) in the current year, (3) the number of utility model patents ($Utility_{i,c,t}$) in the current year, and (4) the number of invention patents ($Invention_{i,c,t}$) in the current year. Among these, patent quality increases in the order of design patents, utility model patents, and invention patents. Because it takes time for innovation inputs to translate into outcomes, we follow Hirshleifer et al. (2013) by lagging innovation inputs by 1 and 2 periods. Consequently, we derive the following proxy variables for firm innovation efficiency:

$$Patent / RD1_{i,c,t} = \frac{Patent_{i,c,t}}{RDratio_{i,c,t-1}},\ Patent / RD2_{i,c,t} = \frac{Patent_{i,c,t}}{RDratio_{i,c,t-2}},$$

$$DP / RD1_{i,c,t} = \frac{Design_{i,c,t}}{RDratio_{i,c,t-1}},\ DP / RD2_{i,c,t} = \frac{Design_{i,c,t}}{RDratio_{i,c,t-2}},$$

$$UP / RD1_{i,c,t} = \frac{Utility_{i,c,t}}{RDratio_{i,c,t-1}},\ UP / RD2_{i,c,t} = \frac{Utility_{i,c,t}}{RDratio_{i,c,t-2}},$$

$$IP / RD1_{i,c,t} = \frac{Invention_{i,c,t}}{RDratio_{i,c,t-1}},\ IP / RD2_{i,c,t} = \frac{Invention_{i,c,t}}{RDratio_{i,c,t-2}}.$$

To ensure the comparability of estimated coefficients, the proxy variables for firm innovation efficiency are standardized in the estimation of regression Eq. (21). Table 10 presents the results. Column (1) reports the impact of housing price appreciation on firm innovation efficiency, measured by the ratio of total patent authorizations to innovation investment lagged by one period ($Patent / RD1_{i,c,t}$). The coefficient of $House_{c,t-1}$ is significantly negative at the 5% level, indicating that housing price appreciation negatively affects firm innovation efficiency. Columns (2) to (4) present analogous results using $DP / RD1_{i,c,t}$, $UP / RD1_{i,c,t}$, and $IP / RD1_{i,c,t}$ as the proxies for firm innovation efficiency, respectively. The coefficients of $House_{c,t-1}$ in Columns (2) and (3) are significantly negative; in Column (4), the coefficient is statistically insignificant. Moreover, the magnitude of the negative impact decreases from Columns (2) to (3). These patterns indicate that housing price appreciation exerts the strongest negative influence on the innovation efficiency of design patents, a more moderate negative effect on that of utility model patents, and no clear effect on that of invention patents. Columns (5) through (8) replicate these analyses using innovation inputs lagged by two periods, producing similar results.

Table 10. The impact of housing price appreciation on firm innovation efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	$Patent\ /\ RD1_{i,c,t}$	$DP\ /\ RD1_{i,c,t}$	$UP\ /\ RD1_{i,c,t}$	$IP\ /\ RD1_{i,c,t}$	$Patent\ /\ RD2_{i,c,t}$	$DP\ /\ RD2_{i,c,t}$	$UP\ /\ RD2_{i,c,t}$	$IP\ /\ RD2_{i,c,t}$
$House_{c,t-1}$	–0.111** (0.045)	–0.098** (0.044)	–0.095** (0.040)	–0.099 (0.079)	–0.065** (0.033)	–0.130** (0.066)	–0.054* (0.028)	–0.028 (0.039)
Constant Term	YES	YES	YES	YES	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
City Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,535	13,379	9,592	10,343	6,637	12,431	7,824	9,064
$Adj-R^2$	0.544	0.512	0.551	0.267	0.840	0.219	0.864	0.186

Note: This table presents the impact of housing price appreciation on firm innovation efficiency. Columns (1) and (5) present the estimation results of regression equation (4), where the ratios of total patent authorizations to innovation investment lagged by 1 period and 2 periods, respectively, are used as proxies for firm innovation efficiency. Columns (2) and (6) report the results using the ratios of design patent authorizations to innovation investment lagged by 1 period and 2 periods as proxies for firm innovation efficiency. Columns (3) and (7) report the results using the ratios of utility model patent authorizations to innovation investment lagged by 1 period and 2 periods as proxies for firm innovation efficiency. Columns (4) and (8) report the results using the ratios of invention patent authorizations to innovation investment lagged by 1 period and 2 periods as proxies for firm innovation efficiency. Robust standard errors clustered at the city-year level are reported in parentheses. Coefficients marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Two important conclusions can be drawn from Table 10. First, housing price appreciation generally reduces firm innovation efficiency. Second, this negative effect is less pronounced for higher-quality innovation projects. Intuitively, firms are more inclined to continue supporting innovation in core projects – even in the face of rising housing prices – recognizing that such high-quality innovations are integral to long-term competitiveness.

6. Conclusions and policy implications

This paper develops a two-sector model, comprising a firm sector and a banking sector, to examine the relationship between housing price appreciation and firm innovation investment, as well as its potential heterogeneity under varying circumstances. Several theoretical predictions arise from the model. First, housing price appreciation exerts a crowding-out effect on firm innovation investment by increasing the opportunity cost of innovation investment. Second, this crowding-out effect is mitigated for firms with stronger debt repayment capabilities or superior R&D capabilities. Third, the crowding-out effect is alleviated in tighter credit environments.

Using a dataset of China's A-share listed companies and 94 cities from 2011 to 2021, we provide robust empirical evidence supporting the theoretical predictions of the proposed model. Furthermore, we identify that the difference in returns between housing investment and innovation investment serves as a key mechanism driving the crowding-out effect. Further analysis highlights the pivotal role of banks in shaping the link between housing price appreciation and firm innovation investment. In particular, the crowding-out mechanism is pronounced only when banks prefer granting more short-term loans or display lower service efficiency. In terms of innovation outcomes, housing price appreciation tends to reduce firm innovation efficiency, with the most substantial negative impact appearing in lower-quality innovation projects.

Several policy implications emerge from this study. First, the government should establish a systematic innovation incentive mechanism to encourage firms to engage in sustained innovation. Specifically, intellectual property protection should be strengthened to safeguard firms' innovation outcomes from infringement or illegal copying, enabling these outcomes to be effectively transformed into economic returns. Additionally, fostering a well-functioning capital market is essential to ensure firms receive adequate returns on innovation, thereby incentivizing technological advancement.

Second, the government should design a multi-layered innovation support system to enhance firms' R&D capabilities. Increased investment in innovation infrastructure is critical, as it provides firms, particularly Small and Medium-Sized Enterprises (SMEs), with shared professional R&D resources necessary for innovation. Furthermore, the government should promote deeper collaboration between research institutions and firms by establishing dedicated funds or offering tax incentives. Leveraging the knowledge reserves of research institutions can strengthen firms' R&D capabilities and accelerate the development of innovative outcomes.

Finally, improving the financial system and credit policies is essential for fostering firm innovation. Although our study indicates that a tight credit environment can help mitigate the crowding-out effect of housing price appreciation on firm innovation investment, it may also restrict financially constrained firms from engaging in innovation activities. Therefore, more flexible policy tools should be developed to balance curbing excessive speculation in the real estate market with supporting firm innovation. For example, differentiated credit policies could be introduced, tightening the overall credit environment while providing targeted financing support to innovative SMEs. This approach would ensure these firms have access to sufficient funding for innovation, even under tight credit conditions.

Despite its contributions, this study has certain limitations. We primarily explore the impact of housing price appreciation on firm innovation from the perspective of firm resource allocation. However, the influence of housing price appreciation on firm innovation operates through multiple channels, many of which are significant but beyond the scope of this study. For instance, housing price appreciation directly increases households' living costs, requiring higher labor income to maintain the same standard of living. This not only raises firms' labor expenses but also indirectly increases production input costs, further squeezing their disposable resources and affecting innovation activities. Additionally, housing price appreciation often leads to increased credit demand from households for home purchases. Since housing mortgage loans are widely regarded as secure, high-quality assets, banks are willing to extend such loans to households. Under limited credit supply, this growing household credit demand may crowd out firms' financing needs, thereby constraining their innovation activities.

Future research could investigate the multidimensional mechanisms through which housing price appreciation affects firm innovation and quantify the specific impact of different channels. Such research would help uncover the layered effects of housing price appreciation on firm innovation, providing policymakers with more comprehensive and detailed evidence for decision-making.

Disclosure statement

The authors declare that they have no conflict of interest.

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APPENDIX

Proof of Equation (10). Further rearranging Eq. (9) yields:

$$F_i(I_i^{RD*})^{\gamma-1}\left(1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right)^{-\frac{\beta}{\beta-1}}-r_h+\left(1-\chi\left(r^*,r_h\right)\right)\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\overline{C}_i=0, \quad \text{(A1)}$$

where $F_i=a_i\gamma\phi(\varpi_i)\left(A_{i0}\right)^{1-\frac{\beta}{\beta-1}}\beta^{-\frac{\beta}{\beta-1}}K_i^{\alpha-\gamma-\frac{\alpha\beta}{\beta-1}}\left(W_i\right)^{\frac{\beta}{\beta-1}}$.

Based on Eq. (A1), we apply the implicit function differentiation method to solve for the partial derivative of I_i^{RD*} with respect to r_h, obtaining:

$$\left\{F_i\left(\gamma-1\right)(I_i^{RD*})^{\gamma-2}\left[1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right]^{-\frac{\beta}{\beta-1}}-\frac{\beta}{\beta-1}F_i(I_i^{RD*})^{\gamma-1}\left[1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right]^{-\frac{\beta}{\beta-1}-1}a_i\phi(\varpi_i)\gamma(\frac{I_i^{RD*}}{K_i})^{\gamma}\frac{1}{I_i^{RD*}}\right\}\frac{\partial I_i^{RD*}}{\partial r_h}=$$
$$1-\left(1-\chi\left(r^*,r_h\right)\right)\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}\partial r_h}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i+\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i. \quad \text{(A2)}$$

Rewriting Eq. (A2) drives:

$$\frac{\partial I_i^{RD*}}{\partial r_h}=\frac{1+\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i-\left(1-\chi\left(r^*,r_h\right)\right)\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}\partial r_h}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i}{F_i\left(\gamma-1\right)(I_i^{RD*})^{\gamma-2}\left(1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right)^{-\frac{\beta}{\beta-1}}-\frac{\beta}{\beta-1}F_i(I_i^{RD*})^{\gamma-1}\left(1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right)^{-\frac{\beta}{\beta-1}-1}a_i\phi(\varpi_i)\gamma(\frac{I_i^{RD*}}{K_i})^{\gamma}\frac{1}{I_i^{RD*}}}. \quad \text{(A3)}$$

Let $G_i=F_i\left(1+a_i\phi(\varpi_i)(\frac{I_i^{RD*}}{K_i})^{\gamma}\right)^{-\frac{\beta}{\beta-1}}(I_i^{RD*})^{\gamma-2}$, and then we can rewrite Eq. (A3) as follows:

$$\frac{\partial I_i^{RD*}}{\partial r_h}=\frac{1+\frac{\partial\chi\left(r^*,r_h\right)}{\partial r_h}\frac{\partial m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i-\left(1-\chi\left(r^*,r_h\right)\right)\frac{\partial^2 m_i\left(I_i^{RD*},r_h\right)}{\partial I_i^{RD*}\partial r_h}\frac{\left(1-d\left(flow_i\right)\right)}{d\left(flow_i\right)}\overline{C}_i}{G_i\left\{\gamma\left[1+\frac{\beta}{1-\beta}\left(1+a_ip(I_i^{RD*})\right)^{-1}a_ip(I_i^{RD*})\right]-1\right\}}. \quad \text{(A4)}$$