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THE IMPACT OF THE DIGITAL ECONOMY ON URBAN HOUSE PRICES: COMPREHENSIVE EXPLORATIONS

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Abstract. Internet technology and data-driven innovations are changing the way people live and work, which could have an impact on real estate supply and demand. Therefore, this study focuses on the relationship between urban digital economy growth and urban house prices. First, the empirical model shows that the digital economy has an inverted U-shaped impact on urban housing prices. The mechanisms underlying this relationship were then examined. The results indicated that fixed asset investment, government expenditure, and the urban environment influence the relationship between digital economy growth and urban house prices. Finally, a heterogeneity analysis revealed that the digital economy does not affect house prices in Tier 1, New Tier 1, and Tier 2 Chinese cities, but increases house prices in Tier 3 cities. In Tier 4 and Tier 5 cities, this relationship was found to be inverted U-shaped. These findings offer valuable insights to policymakers in China in balancing the growth of the digital economy and the stability of house prices.

Keywords: digital economy, housing prices, fixed effect, system GMM, China cities.

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1. Introduction

Housing price fluctuations have a direct impact on the wealth, consumption, and investment behavior of individuals and households, as well as on urban planning and social mobility (Ding et al., 2022). Consequently, studies on housing prices can serve as a valuable reference to the government in its macroeconomic regulation and control. While most existing research has investigated housing prices from a traditional perspective, it is essential to acknowledge the profound impact of the digital economy on the Chinese economy, which has experienced rapid growth. The digital economy is characterized by digitization, informatization, and networking, covering a wide range of fields such as digital industry, digital business, and digital finance. In China, the digital economy is rapidly emerging as an important engine for economic growth, transformation and upgrading, and urbanization. The Chinese government has actively promoted the development of the digital economy via a series of policies and measures, including the "Internet Plus" action plan[1] and the construction of Digital China[2], aiming to accelerate the transformation of informatization and digitization and promote the innovative development of traditional industries. It is also worth emphasizing that the digital economy has revolutionized the way individuals live and work. On one hand, its development has facilitated urbanization and population mobility. This enhances the attractiveness of cities and stimulates demand in the housing market, which can lead to changes in housing prices. On the other hand, the growth of the digital economy has also enabled individuals to engage in online shopping and remote work, granting them greater freedom in choosing their place of residence. As a result, housing demand and prices in urban areas have decreased.

This study argues that the growth of the digital economy can be a significant factor influencing urban housing price changes. However, the impact of the digital economy on housing price fluctuations is complex and dependent on various factors. Against this background, our study aims to fill the gaps in current research and provide a comprehensive understanding of the relationship between the growth of the digital economy and changes in urban housing prices. The study's contributions are mainly reflected in four aspects. First, we thoroughly investigate the relationship between the digital economy and urban house prices, addressing a gap in current research. Second, we examine, in depth, the nonlinear relationship between the digital economy and urban house

[1] State Council of the People's Republic of China. https://english.www.gov.cn/2016special/internetplus/
[2] State Council of the People's Republic of China. https://english.www.gov.cn/policies/latestreleases/202302/28/content_WS63fd33a8c6d0a757729e752c.html

prices, filling another gap in this field. Third, for the first time, we consider the role of three moderating variables, namely fixed asset investment, government expenditure, and urban environment, which deepens the understanding of the mechanism of the digital economy's impact on urban house prices. Finally, we analyze the heterogeneity among Chinese cities, specifically categorizing the sample cities into First-tier, New First-tier, Second-tier, Third-tier, Fourth-tier, and Fifth-tier cities to better reveal the impact of geographic differences on the relationship between the digital economy and urban house prices. This multi-level research design enables this paper to make a comprehensive and unique contribution to the relationship between the digital economy and city house prices. The findings provide valuable references for future research and policy formulation in related fields.

The overall structure of the article is outlined as follows: Section 1 provides an introduction to the article, briefly describing the purpose and significance of the study. Section 2 reviews the relevant literature, encompassing previous studies and the theoretical framework. Section 3 presents the analytical framework and hypotheses utilized in this research. Section 4 presents the data sources and methods utilized in this research. Section 5 reports the empirical findings in detail and provides an in-depth discussion of the results. Finally, Section 6 summarizes the findings and presents relevant policy recommendations.

2. Literature review

Urban housing prices are influenced by numerous factors, reflecting the complex dynamics of housing markets. Extensive research has identified the determinants of housing prices, which can be categorized into several key dimensions. First, economic variables play a fundamental role in determining housing prices, with factors such as fuel prices (Halvorsen & Pollakowski, 1981), macroeconomic aggregates (Baffoe-Bonnie, 1998), income levels (Kok et al., 2018; Jiang & Qiu, 2022), foreign direct investment (Wong et al., 2020), consumer price index (Mohan et al., 2019) and interest rates (Lee & Park, 2022) influencing both demand and supply dynamics within housing markets. Social and demographic characteristics also significantly influence housing prices, with studies having examined the effects of population (Chin & Lee, 2021), school quality (Carrillo et al., 2013), consumption (Wong et al., 2015) and market sentiment (Ding et al., 2023) on urban housing markets. Policy interventions and regulatory frameworks have profound implications for housing markets as well, as land-use constraints (Pollakowski & Wachter, 1990), home-purchase limits (Jia et al., 2018), foreign capital inflows and speculation (Wong et al., 2020), and political uncertainty (Nguyen & Vergara-Alert, 2023) can affect housing affordability and availability. Furthermore, urban development patterns such as tourism development (Cunha & Lobão, 2022; Cong et al., 2023) and urbanization level (Liu et al., 2022) also influence housing markets. Neighborhood characteristics such as railway sound barriers (Lee & Pang, 2022) impact property values and market demand as well. Additionally, emerging technological trends and changes in work patterns are increasingly influencing housing markets, as the rise of teleworking (Schulz et al., 2023) and access to digital infrastructure (Wang et al., 2023a) impact housing preferences and location choices.

In latest research on housing prices, Wu and Deng (2024) used the difference-in-difference method and panel data method to analyze the impact of different urban renewal types on surrounding housing. They found that industrial renewal has the most significant impact on house prices at the beginning and end of renewal, followed by residential renewal and commercial renewal. Rojas (2024) used a hedonic difference-in-difference model to estimate the total and direct effects of railway stations on housing prices and discovered that the total and direct effects promote housing prices. At the same time, Cai et al. (2024) demonstrated that PM2.5 is negatively related to housing prices, while Kim et al. (2024) revealed that green infrastructure has had a positive impact on housing prices recently and air pollution hurts housing prices, supporting Cai et al. (2024). Using data from Croatia, Vizek et al. (2024) found that more intensive tourism demand and housing stock translate into rents and push up house prices. On the other hand, Kim and Wang (2024) used Australian data to show that the growth of the local real exchange rate has a positive impact on house price growth.

However, literature on the relationship between the digital economy and housing prices is scarce, with no known studies on urban housing prices in particular. Therefore, this study analyzed the influence of the digital economy on urban housing prices from a macro perspective, aiming to contribute innovative and distinctive insights. Moreover, while previous studies have explored the non-linear relationship between various factors, including investment demand (Chen et al., 2012), public services (Gan et al., 2021), and school quality (Mathur, 2022), and urban housing prices, there is no known research on the potential non-linear relationship between the digital economy and housing prices. To address this gap in the literature, this study considered the non-linear influence of digital economy growth on urban housing prices.

3. Analytical framework and hypotheses

3.1. Analytical framework

This section aims to discuss how the digital economy may influence urban housing prices. Firstly, the growth of the digital economy can influence housing prices through its impact on businesses. The digital economy has transformed existing industries, encouraged the establishment of new businesses, and created job opportunities. The opening of new offices and stores in urban areas, along with an influx of skilled workers, increases the demand for housing and drives up housing prices in urban areas (Carrillo & Yezer, 2009). However, the digital economy has also facilitated online shopping and remote work, leading to the shift of some businesses from physical stores to online platforms and the adoption of flexible work arrangements. This reduces the demand for housing and can result in lower housing prices in urban areas.

Secondly, the growth of the digital economy can impact housing prices through government actions. As the digital economy develops, governments can support its growth through investments and subsidies, such as investments in high-speed internet connectivity and other digital infrastructure, as well as financial support for digital infrastructure construction, talent training, and technological research and development. Improved internet connectivity and digital infrastructure make cities more attractive for businesses and living, thereby driving up housing prices. Additionally, with the growth of the digital economy, governments can utilize information technology tools for land planning and deployment, enhancing land use efficiency. They can further increase the supply of land and residential units by offering land for sale through public auctions and other market-based methods to address housing supply-demand imbalances and reduce housing prices.

Thirdly, the growth of the digital economy can impact housing prices through the environment. The digital economy promotes the construction of smart cities that leverage big data, artificial intelligence, and other technological means to become intelligent, informative, and sustainable. These smart cities enhance the quality of the urban environment, including air quality and noise pollution. This, in turn, enhances the local living environment and quality of life, leading to higher housing prices. Apart from that, the growth of the digital economy stimulates the green economy and environmental industries, which play a significant role in environmental pollution control and emission reduction. This helps improve the environmental image and quality of cities, attracting more people and businesses to the area and promoting higher housing prices. However, it is important to note that the growth of the digital economy can also pose environmental challenges, such as increased energy consumption and waste emissions, which may negatively affect the environmental quality and living experience of the city and, consequently, have a negative impact on urban housing prices.

3.2. Hypothesis development

This section delves into the formulation of hypotheses regarding the influence of the digital economy on housing prices, aiming to provide a structured framework for analyzing this dynamic relationship. Accordingly, five hypotheses have been put forward as follows.

The digital economy has a significant impact on the economic growth of cities (Goldfarb & Tucker, 2019; Guo et al., 2023). Simultaneously, urban economic growth affects the level of urban housing prices (Kok et al., 2018; Lin et al., 2018). Therefore, this study posited a relationship between the growth of the digital economy and urban housing prices, as follows:

H1: Digital economy growth affects urban housing prices.

Urban housing prices are influenced by various business behaviors, which are closely tied to the growth of the digital economy. From this perspective, the development of the digital economy attracts the establishment of new businesses and encourages existing firms to invest in digital infrastructure, resulting in increased investment in fixed assets. Supporting this notion, Chen et al. (2022) argued that digital economy growth affects urban fixed-asset investment. Additionally, Sun et al. (2022) demonstrated that fixed asset investment impacts urban housing prices. Therefore, it was hypothesized that:

H2a: Digital economy growth increases urban housing prices through businesses' fixed asset investment.

H2b: Digital economy growth decreases urban housing prices through businesses' fixed asset investment.

The development of the digital economy can contribute to economic growth and innovation, leading to increased government revenues and providing more resources and funding for government expenditures (Spence, 2021). As governments recognize the importance of digital infrastructure, they may invest in its development and support digital industries to enhance the competitiveness and attractiveness of cities, subsequently promoting higher housing prices. However, with the growth of the digital economy, governments can also utilize information technology tools for land planning and deployment to improve land use efficiency. They can implement measures to balance the housing market, such as increasing housing supply, improving housing policies and regulations, and providing financial support and subsidies. By enhancing housing supply and implementing effective policies, governments can contribute to a more stable and balanced housing market, potentially dampening house prices. Accordingly, the following hypotheses were proposed:

H3a: Digital economy growth increases urban housing prices through government expenditure.

H3b: Digital economy growth decreases urban housing prices through government expenditure.

The growth of the digital economy has a significant impact on the urban environment (Huang et al., 2023; Jing et al., 2023). It can promote the modernization and intelligence of cities, leading to improvements in environmental quality and human living conditions. However, the digital economy may also result in industrial restructuring and employment transformation in cities, leading to population movement, urban expansion, and land development. These changes can give rise to environmental problems such as urban air pollution, traffic congestion, and the inefficient use of land resources. Consequently, alterations in the urban environment can also influence changes in housing prices (Wang et al., 2022). Thus, the following hypotheses were proposed:

H4a: Digital economy growth increases urban housing prices through the urban environment.

H4b: Digital economy growth decreases urban housing prices through the urban environment.

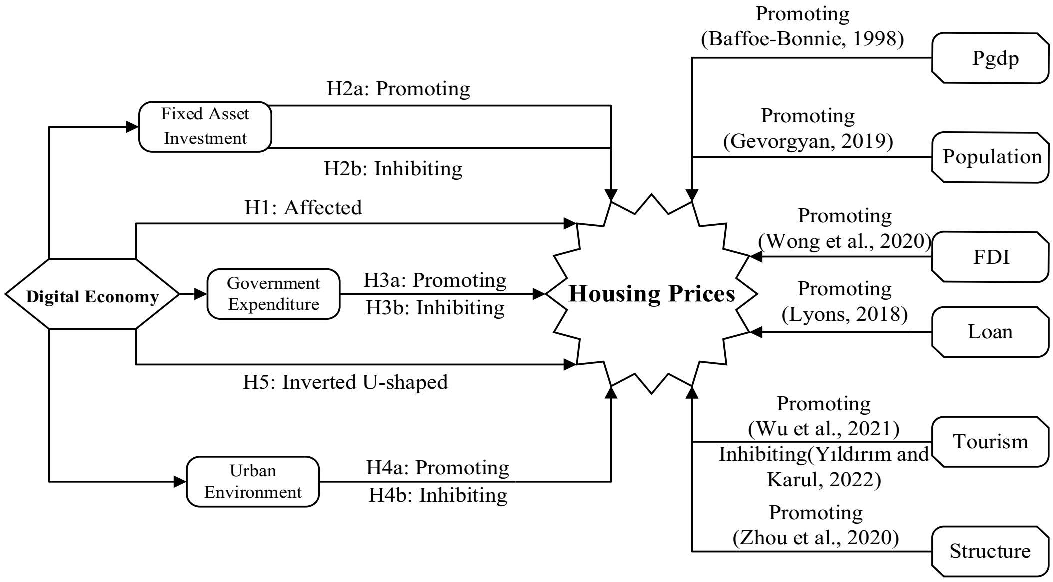

Figure 1. Comprehensive analytical framework

This study predicts an inverted U-shaped relationship between digital economy growth and urban housing prices. Initially, digitalization can drive economic development in cities, increasing their attractiveness and activity levels, thereby leading to a surge in the housing market and higher house prices. However, as the digital economy continues to grow, it may have a dampening effect on housing prices. The growth of the digital economy can reshape the way people work, promoting telecommuting and mobile working, which in turn reduces the demand for central cities and lowers housing prices. Furthermore, the growth of the digital economy can accelerate urbanization, resulting in an increased concentration of the population in cities. This concentration may intensify supply-demand conflicts in urban real estate, thereby exerting downward pressure on housing prices. For instance, urbanization may lead to urban sprawl, increasing the supply of the real estate market in urbanized areas and subsequently dropping housing prices. This study, therefore, hypothesized that:

H5: Digital economy growth has an inverted U-shaped effect on urban housing prices.

To facilitate further understanding of the content and ideas in this paper, a comprehensive analytical framework has been presented in Figure 1. The figure illustrates the relationship between the digital economy and urban house prices, including the interacting mechanisms and other key concepts in this study.

4. Research methodology and data

4.1. Dependent variable

Housing prices (*Prices*): *Prices* was the dependent variable of this research. The proxy of *Prices* was the mean sales price of housing per year at the city level. The data of *Prices* was drawn from China's real estate information network organized by the country's State Information Center.

4.2. Independent variables

Digital Economy (*Digital*): The digital economy was the key variable under investigation in this research. With reference to Chen and Zhang (2023) and Zhao et al. (2020), the Digital Economy Development Index for Chinese cities was chosen as a measure of digital economy growth. This data was taken from the China Urban Statistics Bureau.

4.3. Control variables

Per Gross Domestic Product (*Pgdp*): Economic development is among the most significant influencing factors of housing prices in the city (Baffoe-Bonnie, 1998). Therefore, this study used GDP per capita in Chinese cities to measure their economic growth, with the expectation that higher *Pgdp* boosts urban house prices.

City Population Size (*Population*): The size and dynamics of a city's population have a significant impact on urban housing prices (Gevorgyan, 2019). As the population of a city expands, it can lead to changes in the supply and demand flows within the real estate market, which in turn can drive fluctuations in housing prices. Consequently, this study utilized the total population of Chinese cities as a measure of the cities' population size, with the anticipated outcome that a larger population size positively influences urban housing prices.

Foreign Direct Investment (*FDI*): Foreign direct investment, or FDI, may lead to an increase in local employment opportunities, attracting more people to work and live in the area. This would spike housing demand and contribute to higher housing prices (Wong et al., 2020). In this study, the total annual FDI inflows into a city was utilized as an indicator of the city's FDI level, with the prediction of a positive relationship between *FDI* and urban housing prices.

City Loan Size (*Loan*): The size of loans has a direct impact on the cost of home ownership, with larger loans generally resulting in lower costs and potentially leading to increased housing prices as more individuals can afford homes (Lyons, 2018; Liu, 2023). Conversely, if lending rates increase, the cost of purchasing a home will rise, potentially leading to a decrease in housing prices (Lee & Park, 2022). Therefore, in this study, the size of loans was measured by considering the total loans provided by financial institutions in a city at the year-end. It is anticipated that a higher *Loan* value is positively associated with housing prices.

City Tourism Development (*Tourism*): Tourism development is among the important determinants of house prices changes (Biagi et al., 2015). While Wu et al. (2021) established a positive relationship between tourism development and urban house prices, Yıldırım and Karul (2022) argued for a negative relationship between the two. Therefore, this study used urban tourism revenues to measure cities' tourism development, expecting it to either increase or reduce housing prices.

City Industry Structure (*Structure*): According to Liu and Jiang (2015), improving and integrating a city's industrial structure significantly contributes to the growth of its house prices. Similarly, Zhou et al. (2020) reported that optimizing and upgrading industrial structures serves as the driving force behind the increase in house prices. Therefore, this study referenced the works of Liu and Jiang (2015) and Zhou et al. (2020) to utilize China's Urban Industrial Structure Index as a measure of cities' industrial structures. Data from the China Regional Economic Database was employed for this purpose. It is expected that *Structure* positively influences housing prices.

4.4. Data description

This study utilized panel data that covered 240 cities in China from 2011 to 2019. The data for the variables were sourced from the statistical yearbooks of each respective city, unless otherwise mentioned in Section 4.3. Descriptive statistics for the entire dataset are presented in Table 1. Additionally, tests were conducted to assess multicollinearity. Variance Inflation Factor (VIF) values were calculated for all variables, and the results indicated that all VIF values were below 5. This finding alleviates concerns of bias in the estimates due to multicollinearity. Detailed results can be found in Appendix Table A1.

4.5. Empirical methodology

In this study, a series of fixed effects models were used to conduct the analyses. All variables except *Digital* and *Structure* were taken as logarithms to minimize heteroskedasticity effects. A panel data model was constructed, as shown in Equation (1) and Equation (2). To test hypothesis H5, the squared term of *Digital* was included in the estimated model. If there is an inverted U-shaped relationship, then α_1 and α_2 should be positive and negative, respectively, as well as statistically significant. If not statistically significant, hypothesis H5 would be rejected. Upon ruling out the inverted U-shaped effect, *Digital's* squared term would be eliminated from the model, and a new model would be set up as in Equation (3) for re-estimation.

$$\mathrm{Ln}\left(Prices_{it}\right) = \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \mu_i + \nu_t + \varepsilon_{it}; \quad (1)$$

$$\mathrm{Ln}\left(Prices_{it}\right) = \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}; \quad (2)$$

$$\mathrm{Ln}\left(Prices_{it}\right) = \alpha_0 + \alpha_1 Digital_{it} + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (3)$$

In Equation (1), μ_i and ν_t are the effects of city and time, respectively. To ensure the reliability of the benchmark estimation results, several robustness checks were conducted. Due to potential unobserved limitations in the research design, the benchmark regression results on the effect of the digital economy on housing prices could be a mere placebo. As such, following the approach outlined in Ding et al. (2023), a placebo test was carried out. This involved removing all data from the sample and then randomly redistributing the data. Equation (2) was re-estimated using this modified dataset. If the relationship between the digital economy and urban house prices in the original model is not a placebo effect, the results of the placebo test should not indicate a causal relationship of the same magnitude.

Additionally, Ding et al. (2022) identified a critical limitation of the general panel fixed effects model, in that it assumes a normal distribution among variables. To examine whether the impact of digital economy growth on urban housing prices remains significant under a different distribution assumption, robustness testing was conducted using a Poisson model, represented by Equation (4).

$$Prices_{it} = \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}. \quad (4)$$

Table 1. Descriptive statistics of full sample

Category	Variable name	Measurement	Mean	Standard Deviation	Min	Max	Expected sign
Dependent variable	*Prices*	RMB	5781.625	4020.305	1951.08	55797	
Independent variable	*Digital*	Index	0.0333	0.7330	–1.2062	9.8023	
Control variables	*Pgdp*	RMB	52731.95	30710.9	6647	215488	+
	Population	10,000 people	4594517	3302071	195000	3.42e+07	+
	FDI	US$ million	101264.5	233710.9	1	3082564	+
	Loan	Million of RMB	3562.447	7348.081	91.2034	83761.3	+
	Tourism	Million of RMB	44347.97	64827.26	460.4664	622403.9	+/–
	Structure	Index	0.9684208	0.5538594	0.1750152	5.168317	+

Cong et al. (2024) and Saydaliev and Chin (2023) have acknowledged that the fixed effects model serves as a reliable benchmark regression model, providing a reasonable range of static estimates. However, the static estimation approach fails to account for potential endogeneity concerns arising from the correlation between the digital economy and urban housing prices. This can lead to biased estimation results. In order to address this endogeneity issue, this study followed the recommendation of Arellano and Bond (1991) and employed a systematic Generalized Method of Moments (GMM) approach in the panel data model. In this approach, lagged values of the explanatory variables were utilized as instrumental variables to address endogeneity.

$$\mathrm{Ln}(Prices_{i,t}) = \alpha_0 + \alpha_1 \mathrm{Ln}\left(Prices_{i,t-1}\right) + \alpha_2 Digital_{i,t} + \alpha_3 (Digital_{i,t})^2 + \beta Z_{i,t} + \varepsilon_{i,t}. \quad (5)$$

In Equation (5), $\mathrm{Ln}\left(Prices_{i,t-1}\right)$ is the lagged value of the explained variable, Z is a set of control variables that can impact the digital economy, and $\varepsilon_{i,t}$ it is the error term. α_0, α_1, α_2, α_3, and β are the coefficients to be estimated.

5. Empirical findings and discussion

5.1. Baseline regression results

This study initially estimated Equations (1) and (2) using panel fixed effects models. The results of these estimations are presented in Table 2, specifically in Column I and Column II. Column I displays the findings without considering the control variables, while Column II includes all the control variables. The analysis revealed that in all models, the coefficient for the variable *Digital* was positive, while the coefficient for the squared term of *Digital* was negative. Furthermore, both coefficients were statistically significant at the 1% level. These results suggest that digital economy growth affects urban housing prices, providing support for hypothesis H1. Additionally, the relationship may exhibit an inverted U-shape. To investigate this relationship further, a U-test was conducted using data from all cities. The results, presented in Appendix Table A2, confirm the inverted U-shaped association between the digital economy and urban housing prices, thus validating hypothesis H5.

Regarding the control variables in the main model (Column II), the coefficients for *Pgdp*, *Population*, *FDI*, *Loan*, and *Structure* were all positive and statistically significant. This indicates that urban economic development, population growth, increased FDI, urban loan expansion, and urban industrial restructuring are factors that contribute to higher housing prices. This is in line with the study of Vaidyanathan et al. (2023), which found that economic growth is one of the important factors contributing to house prices. This paper also supports the finding of Lin et al. (2018) that population growth has a promoting effect on urban house prices, as well as that of Liu (2023) that the size of loans has a promoting effect on house price growth. Additionally, this paper finds that FDI promotes house price growth, which is consistent with the works of Chang et al. (2018) and Ahmed and Jawaid (2023), further validating that FDI is one of the factors affecting house prices. Moreover, the coefficients for *Pgdp* and *Population* were 0.1398 and 0.1681, respectively, suggesting that urban economic development and population size have a greater impact on housing prices compared to FDI, loans, and industrial structure. On the other hand, *Tourism* showed a negative, albeit statistically significant, coefficient. This supports the findings of Alola et al. (2020) and Cong et al. (2023), which suggest that tourism development suppresses urban housing prices. The growth of tourism may increase the supply of housing in an area to meet the demand for tourist accommodation. This increased supply can lead to a more balanced real estate market in terms of supply and demand, consequently dampening the increase in house prices.

5.2. Endogenous solutions

The results of the baseline regressions may suffer from an endogeneity problem: the growth of urban housing prices may also have an inverse effect on the development of the digital economy. In this study, we used the cross-multiplier of the number of post offices per 100 people in each sample city in 1984 and the number of Internet users in each sample city in the previous year as instrumental variables to address the potential endogeneity problem. The number of post offices has the following effects on the development of the digital economy: first, more post office coverage can drive remote and rural residents to participate in the digital economy (Huang et al., 2019). Where other digital service infrastructures are lacking, post offices, as traditional service providers, can provide residents with access to the digital economy, facilitating their participation in online shopping, digital payments, and other digital transactions (Deng et al., 2023). From this perspective, there is a correlation between the distribution of post offices and the development of the digital economy. In addition, with the development of information technology, post offices are gradually becoming obsolete and cannot directly impact a city's house prices, thus better satisfying the exclusivity of the instrumental variable. Therefore, the two-stage least squares method was used to test it, and the test results are shown in Column III of Table 2. Firstly, the explanatory variables in the model were tested for endogeneity and the results showed that the DWH test statistic was 80.21, significant at the 1% level (p = 0.000 < 0.01); therefore, the original hypothesis that all the explanatory variables are exogenous was rejected, and instead, it is argued that there was an endogeneity problem in the explanatory variables. The validity of the instrumental variables was further tested, and the results showed that the Shea partial R^2 of both instrumental variables was around 0.1, indicating no weak instrumental variable problem. According to the results of the two-stage least squares test, the digital economy has a significant positive effect on urban house prices, and the squared term of the digital economy significantly suppresses the effect on urban house prices, proving that the benchmark results are robust.

In addition, this study again attempted to test for endogeneity and then applied two-stage least squares analysis via instrumental variables to address any arising endogeneity issues. Specifically, referring to Wang et al. (2023b), the lagged first-order term of the explanatory variable "digital economy" was used as an instrumental variable to solve the endogeneity problem through the two-stage least squares method. The validity of an instrumental variable requires that it satisfies both exogeneity and endogeneity conditions to ensure that no new bias is introduced. In terms of homogeneity, the lagged first-order term for the digital economy was chosen because it is not directly affected by house prices, thus avoiding the introduction of new causality bias. At the same time, the term satisfies the endogeneity condition because it reasonably represents or reflects the reality of economic freedom. Therefore, the choice of the lagged first-order term for the digital economy as an instrumental variable is justified because it fulfils the homogeneity and endogeneity conditions. The results in Column IV show that the DWH test statistic is 94.17, significant at the 1% level (p = 0.000 < 0.01), and the Shea partial R^2 of both instrumental variables is around 0.1. Thus, it is concluded that there was no weak instrumental variable problem. According to the results of the two-stage least squares test, the digital economy makes a significant contribution to urban house prices, and the squared term of the digital economy significantly suppresses the effect on urban house prices, proving once again that the benchmark results are robust.

5.3. Robustness checks results

To check the robustness of the baseline regression findings, relevant tests were performed, the results of which are presented in Columns V to VIII of Table 2. In Column V,

Table 2. Baseline regression and robustness check results

	Baseline regression		Endogenous solutions		Robustness checks			
	Fixed effect		Two-stage least squares	Two-stage least squares (lagged first-order term)	Add control variables	Placebo effect	Poisson effect	SYS-GMM
	I	II	III	IV	V	VI	VII	VIII
$Digital_{it}$	0.0608***	0.0434***	0.3440***	0.2740***	0.0563***	0.0045	0.0997***	0.0781***
	(4.8912)	(3.5601)	(9.7296)	(6.5072)	(4.5906)	(1.4692)	(76.3996)	(6.4428)
$(Digital_{it})^2$	–0.0065***	–0.0049***	–0.1183***	–0.0034***	–0.0152***	0.0002	–0.0101***	–0.0039***
	(–3.8665)	(–2.9674)	(–2.6577)	(–3.7664)	(–9.1124)	(0.2256)	(–68.9857)	(–3.9992)
Ln($Pgdp_{it}$)		0.1398***	0.1564***	0.1695***	0.1919***	0.1500***	0.3002***	0.1661***
		(6.8179)	(3.9224)	(4.2253)	(9.7641)	(7.3786)	(108.1290)	(5.0178)
Ln($Population_{it}$)		0.1681***	0.2546	0.2456**	0.0475**	0.1771***	0.5242***	0.3121***
		(3.6458)	(0.9281)	(2.1567)	(2.3091)	(3.8366)	(100.5777)	(3.3272)
Ln(FDI)$_{it}$		0.0069**	–0.0017	0.0012	0.0001	0.0073**	–0.0095***	0.0046*
		(2.3836)	(–0.4483)	(0.3560)	(0.0485)	(2.5136)	(–22.5074)	(1.6942)
Ln($Loan_{it}$)		0.0657***	0.0882**	0.0464**	0.1009***	0.0631***	0.1149***	0.0447***
		(4.8837)	(2.3996)	(2.2466)	(10.1092)	(4.6852)	(77.4822)	(5.5595)
Ln($Tourism_{it}$)		–0.0486***	–0.0485**	0.0098	0.0392***	–0.0495***	0.0131***	0.0923***
		(–4.8782)	(–2.4409)	(0.2216)	(4.5108)	(–4.9685)	(11.1811)	(6.5345)
$Structure_{it}$		0.0333***	0.0673*	0.0723***	0.1005***	0.0362***	0.1342***	0.0810***
		(2.9853)	(1.9529)	(3.0390)	(9.4955)	(3.2501)	(102.5344)	(5.4647)
Ln(CPI_{it})					0.7610***			
					(4.6396)			
Ln($Urban_{it}$)					0.1123***			
					(3.0276)			
Constant	8.3394***	4.2466***	4.2805	3.8574**	–4.0689***	3.9849***	–3.5252***	–1.1743
	(840.2513)	(5.7860)	(1.1509)	(2.4555)	(–3.6061)	(5.4381)	(–41.8764)	(–0.8543)
Ln($Price$)$_{i,t–1}$								0.2131***
								(8.6018)
R-squared	0.721	0.739	0.758	0.810	0.770	0.738		
DWH			80.21(p = 0.000)	94.17(p = 0.000)				
Shea's partial R^2			0.8392($Digital$)	0.8442($Digital$)				
			0.8185($Digital^2$)	0.8212($Digital^2$)				
Sargan test								0.102
AR(1)								0.000
AR(2)								0.754

Notes: t-statistics are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. SE statistics in parentheses.

we incorporated insights from Mohan et al. (2019) and Liu et al. (2022), who highlighted the significance of the consumer price index and urbanization levels in influencing urban house prices. Consequently, we augmented the baseline model (2) by including these variables and reestimating the model. The results in Column V show that the coefficients of *Digital* and *Digital squared*, along with consumer price index and urbanization level, are all significant at the 1% significance level. This proves the stability of the benchmark results and reaffirms the importance of the consumer price index and urbanization level in influencing urban house prices. In Column VI, the results of the placebo test show that the coefficients of *Digital* were mostly statistically insignificant and differed significantly from the baseline estimates, indicating that the result of the baseline model was not a placebo effect. The Poisson regression results in Column VII and the System GMM estimation results in Column VIII also corroborate the benchmark regression results. The above robustness tests validate the reliability and accuracy of the baseline regression. In addition, the lagged variable for *Digital* demonstrated a statistically significant (at the 1% level) positive coefficient, revealing that cities with better digital economies may also have higher housing prices in the future.

5.4. Further analysis

5.4.1. Mechanism analysis

Building upon extant research, this study focused on examining how digital economy growth impacts urban house prices. As discussed earlier, this effect can operate through three main channels: business fixed asset investment, government spending, and the urban environment. This section presents the empirical investigation of whether digital economy growth influences urban house prices through these three mechanisms. To measure business fixed asset investment, government spending, and the urban environment, this study utilized total urban fixed asset investment (*UFAI*), total government expenditure (*Government*), and urban PM2.5 concentration (*Environment*), respectively, the data of which was sourced from the cities' statistical yearbooks.

Initially, fixed effects regression tests were conducted on fixed asset investment, government expenditure, and the urban environment, excluding the digital economy, to establish the relationships between these factors and urban housing prices. Specifically, to examine whether digital economy growth affects urban house prices through urban fixed asset investment, as shown in Equation (6), the study included the interaction term between the digital economy and urban fixed asset investment (*Digital**Ln(*UFAI*)) in Equation (2). Similarly, (*Digital*)*Ln(*Government*) and (*Digital*)*Ln(*Environment*) were incorporated into Equation (2) to obtain Equations (7) and (8), respectively. All the variables in Equations (6) to (8) remained consistent with those in the baseline regression.

$$\begin{aligned}\mathrm{Ln}\left(Prices_{it}\right) &= \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \\ &\alpha_3\left(\left(Digital_{it}\right) * \mathrm{Ln}\left(UFAI_{it}\right)\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it};\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{Ln}\left(Prices_{it}\right) &= \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \\ &\alpha_3\left(\left(Digital_{it}\right) * \mathrm{Ln}\left(Government_{it}\right)\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it};\end{aligned} \tag{7}$$

$$\begin{aligned}\mathrm{Ln}\left(Prices_{it}\right) &= \alpha_0 + \alpha_1 Digital_{it} + \alpha_2 (Digital_{it})^2 + \\ &\alpha_3\left(\left(Digital_{it}\right) * \mathrm{Ln}\left(Environment_{it}\right)\right) + \beta Z_{it} + \mu_i + \nu_t + \varepsilon_{it}.\end{aligned} \tag{8}$$

Table 3 presents the estimated mechanisms for the relationship between the digital economy and urban house prices. Columns I and II show the estimated results of the moderating effect of fixed asset investment on the relationship between the digital economy and urban house prices. In Column II, the interaction term (*Digital*)*Ln(*UFAI*) obtained a positive coefficient at the 1% significance level, supporting hypothesis H2a that the digital economy promotes urban housing prices through business activities. This suggests that the development of the digital economy is usually accompanied by the rise of new technologies and industries, such as the Internet, artificial intelligence, and e-commerce, and that the development of these new industries drives increased investment in commercial fixed assets. Enterprises have an increasing demand for digital and intelligent commercial facilities, such as smart office buildings, data centers, and technology parks. The construction of and investment in commercial fixed assets enhance commercial activities in cities and drive the development of related industrial chains. Increased investment in commercial fixed assets expands employment opportunities, attracting more citizens into the city and increasing the demand for housing. With the increase in job opportunities and the population, the demand side of the real estate market is boosted, driving up house prices (Ding et al., 2022). Increased investment in commercial fixed assets also means increased demand for commercial land, hiking prices in the commercial real estate market, which in turn affects the overall real estate market. Thus, the digital economy indirectly drives up urban house prices by boosting commercial fixed asset investment, reflecting the close relationship between the digital economy and the real estate market.

Columns III and IV present the estimation results of the moderating effect of government expenditure on the impact of digital economic growth on urban house prices. Notably, in Column IV, the interaction term (*Digital*)*Ln(*Government*) obtained a significant positive coefficient at the 1% significance level, supporting hypothesis H3a that digital economy growth promotes urban housing prices through government action. The expansion of the digital economy can generate additional tax revenue for the government, enabling increased government expenditures and investments in infrastructure projects. These construction activities stimulate related industries, potentially leading to job growth and attracting more individuals to the area in search of employment. This, in turn, increases the demand for housing, thereby driving up house prices.

Columns V and VI present the estimation results of the moderating effect of the urban environment on the

Table 3. Mechanism tests

	Fixed Asset Investment		Government		Environment	
	I	II	III	IV	V	VI
$Digital_{it}$		0.1315**		0.1724***		0.1356***
		(2.1624)		(3.2765)		(2.7342)
$(Digital_{it})^2$		–0.0056***		–0.0073***		–0.0048***
		(–3.3593)		(–4.1007)		(–2.9160)
Ln($Pgdp_{it}$)	0.1095***	0.0922***	0.1120***	0.0938***	0.1449***	0.1336***
	(4.5482)	(3.7965)	(5.0165)	(4.1779)	(7.0883)	(6.4892)
Ln($Population_{it}$)	0.1424***	0.1032**	0.1264***	0.0810*	0.1750***	0.1483***
	(3.0127)	(2.1347)	(2.6597)	(1.6777)	(3.7951)	(3.1491)
Ln$(FDI)_{it}$	0.0057*	0.0051*	0.0058**	0.0051*	0.0072**	0.0075**
	(1.9384)	(1.7442)	(1.9983)	(1.7407)	(2.4790)	(2.5612)
Ln($Loan_{it}$)	0.0630***	0.0674***	0.0599***	0.0650***	0.0640***	0.0664***
	(4.6867)	(5.0245)	(4.4530)	(4.8523)	(4.7521)	(4.9465)
Ln($Tourism_{it}$)	–0.0576***	–0.0489***	–0.0548***	–0.0420***	–0.0516***	–0.0512***
	(–5.6072)	(–4.6261)	(–5.4719)	(–4.0570)	(–5.1604)	(–5.1314)
$Structure_{it}$	0.0354***	0.0305***	0.0331***	0.0254**	0.0354***	0.0307***
	(3.1810)	(2.7357)	(2.9714)	(2.2778)	(3.1759)	(2.7412)
Ln($UFAI_{it}$)	0.0326***	0.0301***				
	(3.1491)	(2.9158)				
$(Digital_{it})^*$Ln($UFAI_{it}$)		0.0145***				
		(2.9330)				
Ln($Government_{it}$)			0.1032***	0.0893***		
			(4.0918)	(3.5403)		
$(Digital_{it})^*$Ln($Government_{it}$)				0.0203***		
				(4.1457)		
Ln($Environment_{it}$)					–0.0706**	–0.0704**
					(–2.3990)	(–2.3981)
$(Digital_{it})^*$Ln($Environment_{it}$)						–0.0255*
						(–1.9293)
Constant	4.6704***	5.3886***	4.2339***	5.1214***	4.3723***	4.8952***
	(6.1432)	(6.9288)	(5.7849)	(6.8429)	(5.8531)	(6.4094)
R-squared	0.739	0.741	0.740	0.743	0.738	0.740

Notes: t-statistics are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

relationship between digital economic growth and urban house prices. In Column VI, the interaction term (*Digital*)*Ln(*Environment*) obtained a statistically significant negative coefficient, supporting hypothesis H4b that digital economy growth inhibits housing prices through the urban environment. The digital economy facilitates the application of environmental monitoring and management technologies. Through sensors, data analysis, and smart city management systems, cities can monitor and manage air quality in real-time. Improved air quality heightens individuals' preference to live in such cities, reducing the housing demand in other areas and mitigating upward pressure on house prices (Mariel et al., 2022). Additionally, digital economy growth drives innovation in sustainable transportation and intelligent traffic management. Applications such as shared mobility services, electric vehicles, and intelligent traffic signal systems have reduced private vehicle usage, alleviating traffic congestion and exhaust emissions. Digital technologies have also enhanced traffic flow scheduling and management, improving overall traffic efficiency. This enables smoother travel for city dwellers and reduces the necessity of residing in congested areas, thereby reducing competition in the real estate market and curbing the rise in house prices.

5.4.2. Heterogeneity analysis

China comprises numerous cities with varying levels of economic development and distinct economic, social, and policy environments. Consequently, there is a significant disparity in property prices among cities of different levels (Chin & Li, 2021). Analyzing the heterogeneity across cities at different levels can help the government understand the characteristics and challenges of the real estate market in each level. This understanding enables the formulation of appropriate regulatory policies to stabilize the market, mitigate risks, and promote sustainable development. Therefore, to comprehensively examine the heterogenous effects of the digital economy on house prices across cities, this study divided the sample Chinese cities into six sub-samples: Tier 1, New Tier 1, Tier 2, Tier 3, Tier 4, and Tier 5. This categorization was based on the cities' degree of economic development and China's 2022 City Business Attractiveness Ranking. Please refer to Appendix Table A3 for the list of cities.

As depicted in Table 4, the results indicate that the digital economy does not significantly affect house price changes in Tier 1, New Tier 1, and Tier 2 Chinese cities. The relatively high demand for real estate and limited supply in China's first-tier cities, driven by their economic dynamism and concentrated population, generally result in higher house prices regardless of digitalization. On the other hand, house prices in New Tier 1 and Tier 2 cities are influenced by supply and demand dynamics and land policies specific to each city, with the digital economy playing a relatively minor role in shaping these factors. In Tier 3 cities in China, the squared term of *Digital* was negative but not statistically significant. This suggests that the digital economy in Tier 3 cities may not exhibit a non-linear effect on urban house prices. Therefore, the relationship was then tested in linear form. As shown in Column IVa, in third-tier Chinese cities, digital economy growth contributes to higher urban house prices. The digital economy enhances the economic vitality of these cities, attracting external investments and inflows of talent while creating new industrial opportunities. This, in turn, stimulates the city's economy and drives up house prices. Additionally, the development level, geographic location, and industrial structure of Tier 3 cities in China are diverse, which leads to variations in the impact of digital economy growth on house prices depending on the specific characteristics of each city. Notably, some Tier 3 cities may exhibit a greater dependence on the digital economy, resulting in more pronounced fluctuations in house prices.

According to the findings in Table 4, in Tier 4 and Tier 5 cities, the coefficient of *Digital* and the squared term of *Digital* were both statistically significant, with a positive and negative sign, respectively. This suggests an inverted U-shaped relationship between the digital economy and urban house prices in these cities. The existence of this inverted U-shaped effect was further supported by the results of the U-test, as presented in Appendix Table A2. Next, this study aimed to identify the inflection point at which the relationship transitions from positive to negative. According to the U-test results, the inflection point of the digital economy against urban house prices in Tier 4 cities was 0.60. This indicates that the digital economy suppresses urban house prices when the level of digital economy growth in Tier 4 cities exceeds 0.6. By the end of 2019, 14 cities in China's fourth-tier category, including Lishui, Longyan, Quzhou, Yulin, Xining, Meizhou, Shaoguan, Zhoushan, Beihai, Jinzhou, Dongying, Lvliang, Neijiang, and Jincheng, had digital economy growth levels above

Table 4. Heterogeneity analysis

	First-tier cities	New first-tier cities	Second-tier cities	Third-tier cities	Third-tier cities	Fourth-tier cities	Fifth-tier cities
	I	II	III	IV	IVa	V	VI
$Digital_{it}$	0.0669	–0.0052	–0.0509	0.0638**	0.0563***	0.0530**	0.0889***
	(1.2183)	(–0.1207)	(–1.0836)	(2.4529)	(3.2394)	(2.0906)	(2.7369)
$(Digital_{it})^2$	–0.0045	–0.0058	0.0112	–0.0038		–0.0442***	–0.0792***
	(–1.1000)	(–0.8764)	(1.0955)	(–0.3891)		(–3.0561)	(–3.3535)
Ln($Pgdp_{it}$)	1.0701***	0.2207	–0.1845*	–0.1071**	–0.1048**	0.1526***	0.0197
	(3.5069)	(1.3910)	(–1.6944)	(–2.1538)	(–2.1240)	(4.5981)	(0.5179)
Ln($Population_{it}$)	0.2803	0.6096***	0.6162**	0.1383	0.1337	–0.2057***	0.2197
	(1.0792)	(2.8898)	(2.3813)	(1.1605)	(1.1284)	(–3.3254)	(1.5770)
Ln(FDI)$_{it}$	0.1684*	–0.0348	0.0096	–0.0080	–0.0074	0.0066	0.0083*
	(1.8553)	(–1.0209)	(0.7509)	(–1.3846)	(–1.3304)	(1.2667)	(1.8812)
Ln($Loan_{it}$)	0.5467*	0.3739***	0.3274***	0.0519**	0.0520**	0.0392*	0.0448
	(1.9578)	(2.9173)	(4.8515)	(2.4086)	(2.4195)	(1.9422)	(1.5937)
Ln($Tourism_{it}$)	–0.5710**	-0.2208***	0.0054	–0.0854***	–0.0855***	–0.0166	0.0196
	(–2.8558)	(–2.7692)	(0.1076)	(–4.7662)	(–4.7795)	(–1.0899)	(0.9535)
$Structure_{it}$	–0.1126	0.0810	–0.0558	0.0517**	0.0511**	0.0878***	0.0018
	(–1.3473)	(1.2991)	(–1.2381)	(2.2432)	(2.2240)	(3.6918)	(0.1046)
Constant	–7.6869	–3.7224	–1.5695	7.7788***	7.8133***	9.5318***	4.2577**
	(–1.3575)	(–0.9750)	(–0.4024)	(4.0707)	(4.0969)	(9.0218)	(2.1211)
R-squared	0.950	0.862	0.754	0.840	0.841	0.782	0.627

Notes: t-statistics are in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

0.6. This implies that the digital economy in these cities has had a suppressive effect on urban house prices. Similarly, the inflection point of the digital economy against urban house prices in Tier 5 cities was 10.88, inferring that urban house prices are pushed downward when the level of digital economy growth in Tier 5 cities surpasses 10.88. As of the end of 2019, none of the 61 fifth-tier cities in the sample had a digital economy growth level of 10.88. Thus, it can be surmised that digital economy growth currently boosts house prices in fifth-tier cities and does not inhibit them.

Regarding the control variables, an interesting finding emerged. Urban economic growth was found to be a significant driver of house prices in Tier 1 and Tier 4 cities. Conversely, urban economic growth was found to significantly dampen house prices in Tier 2 and Tier 3 cities. This can be attributed to the fact that Tier 1 cities are typically national economic and financial centers with higher levels of economic development and larger economies. On the other hand, Tier 4 cities, while relatively smaller, play an important role in regional economic development. These cities experience faster economic growth, attracting substantial capital and population inflows, which drive the demand for real estate and contribute to rising house prices. In contrast to first and fourth-tier cities, second- and third-tier cities have more modest economic sizes and development levels. Economic growth in these cities tends to be slower, and they may face challenges such as industrial restructuring and population outflows, which can curb the rise in house prices. This is consistent with the finding of Chin and Li (2021) and Li et al. (2021) that differences in house price increases across Chinese cities are due to a variety of factors, such as regional economic development, population growth, and supply and demand. Additionally, government regulatory measures may be implemented in these cities to limit excessive price increases and maintain market stability.

6. Conclusions

This study has evaluated the impact of digital economy growth on urban house prices in 240 Chinese cities from 2011 to 2019 using various statistical techniques, including fixed effects models, placebo tests, Poisson regression, and system GMM. The findings indicate an inverted U-shaped relationship between digital economy growth and urban house prices. Control variables such as city GDP per capita, FDI, city population size, and total city loans were included to account for factors that may affect housing prices. Economic growth, FDI, and population size were identified as significant contributors to higher housing prices, while urban tourism development was found to restrain the rise of house prices. Furthermore, by incorporating mediating mechanisms, the study reveals that digital economy growth influences housing prices through business fixed asset investment, government expenditure, and the urban environment. Finally, the study examined the heterogeneity of the digital economy's impact on urban house prices across six tiers of cities, revealing varying relationships. Specifically, the results showed that the digital economy does not affect house prices in China's Tier 1, New Tier 1, and Tier 2 cities, but has a positive effect in China's Tier 3 cities and a non-linear, inverted U-shaped effect in China's Tier 4 and Tier 5 cities.

The findings of this study provide valuable insights for the Chinese government in promoting digital economy growth while ensuring stability in house prices. First, given that urban tourism development has been found to suppress house prices, the government can increase investments in tourism infrastructure (e.g., hotels, tourist attractions, and transportation networks) to attract more tourists to the city, boost tourism demand, and stimulate the local economy. Second, as the study shows that loan size plays a crucial role in driving up house prices, the government can implement stricter loan conditions and requirements by strengthening loan regulation and management. This could involve increasing the downpayment ratio, lowering loan limits, or tightening loan eligibility criteria to reduce the availability of loans and curb the rise in house prices. Third, the government can adjust its focus areas for fiscal spending by allocating more resources to public infrastructure, education, healthcare, and other social welfare sectors, rather than predominantly focusing on real estate-related projects. This approach would reduce the stimulus to the real estate market and help prevent excessive increases in property prices. Lastly, the government can promote the adoption of energy-efficient technologies and digital energy-saving solutions in digital transformation efforts. By encouraging businesses and individuals to embrace these technologies, energy efficiency can be improved, energy waste can be reduced, and the negative impact on the environment can be minimized. This, in turn, can lead to cost savings in production and stronger business competitiveness, ultimately contributing to the stabilization of house prices.

To ensure a stable and sustainable impact of the digital economy on housing prices, governments, particularly in China's fourth and fifth-tier cities, can consider the following policy recommendations. Since digital economy growth requires suitable office and innovation spaces, the government can facilitate it by increasing the supply of land and optimizing land planning, creating favorable conditions for digital economy enterprises. By addressing the tight land supply situation, the government can prevent housing prices from rising excessively due to imbalances between supply and demand. Additionally, the government can reinforce its support for technological innovation by encouraging research and development activities in areas related to the digital economy, such as through increased funding and incentives to foster innovation. Moreover, the government should prioritize the training and recruitment of talent for the digital economy. By strengthening policies that attract and nurture skilled professionals, the government can meet the growing demands of the digital economy, enhance market supply flexibility, and alleviate the upward pressure on property prices.

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Competing interests

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Availability of data

Authors provide data on request.

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Appendix

Table A1. Multicollinearity test

Variable name	VIF	1/VIF
Pgdp	3.53	0.283286
Population	3.44	0.290697
Loan	3.35	0.298507
Tourism	3.01	0.332225
Digital	2.72	0.367647
FDI	2.03	0.492611
Structure	1.45	0.689655
Mean VIF	2.79	

Table A2. U-test

	All cities		Fourth-tier cities		Fifth-tier cities	
Extreme point	4.68		0.60		10.88	
	Lower	Upper	Lower	Upper	Lower	Upper
Interval	–1.21	9.80	–0.98	2.13	6.66	13.34
Slope	0.08	–0.07	0.14	–0.14	–0.03	0.02
t-value	4.81	–2.78	2.95	–2.60	–4.47	1.87
$P > t$	0.00	0.00	0.00	0.00	0.00	0.00
t-value	2.78		2.60		1.87	
P	0.00		0.00		0.00	

Test: H_1: Inverse U-shape vs. H_0: Monotone or U-shape

Table A3. City list

First-tier cities	Beijing, Guangzhou, Shanghai, Shenzhen
New first-tier cities	Chengdu, Changsha, Chongqing, Donguan, Foshan, Hefei, Hangzhou, Ningbo, Nanjing, Qingdao, Tianjin, Xian, Wuhan, Zhangzhou
Second-tier cities	Changchun, Dalian, Fuzhou, Guiyang, Haerbin, Huizhou, Jinan, Jinhua, Jiaxing, Kunming, Lanzhou, Linyi, Nanchang, Nanning, Quanzhou, Shaoxing, Shenyang, Shijiazhuang, Taiyuan, Wuxi, Weifang, Wenzhou, Xiamen, Xuzhou, Yantai, Zhuhai, Zhongshan
Third-tier cities	Anqing, Anyang, Bangbu, Chuzhou, Chaozhou, Dezhou, Fuyang, Guilin, Ganzhou, Heze, Haikou, Huhehaote, Huzhou, Hengyang, Jinzhou, Jiujiang, Jiangmen, Jieyang, Kaifeng, Luoyang, Liaocheng, Liuan, Liuzhou, Mianyang, Ningji, Ningde, Nanyang, Putian, Qingyuan,- Shantou, Shangqiu, Sanya, Shangrao, Suzhou, Tangshan, Taian, Taizhou, Wuhu, Weinan, Wulumuqi, Xiangyang, Xinxiang, Xintai, Xinyang, Xuchang, Xianyang, Yuncheng, Yinchuan, Yueyang, Yichang, Yichun, Yancheng, Zibo, Zhenjiang, Zhoukou, Zhunyi, Zhanjiang, Zhumadian, Zhaoqing, Zhuzhou
Fourth-tier cities	Anshan, Baotou, Binzhou, Beihai, Baise, Baoji, Binzhou, Bozhou, Changde, Changzhi, Cifeng, Datong, Deyang, Daqing, Dongying, Dandong, Dazhou, Ezhou, Eerduosi, Fuzhou, Huangshi, Hanzhong, Huainan, Huaibei, Huanggang, Heyuan, Jingdezhen, Jincheng, Jiaozuo, Jilin, Jian, Jinzhou, Jinzhong, Lvliang, Longyan, Luohe, Lishui, Leshan, Luzhou, Linyi, Loudi, Meizhou, Maoming, Meishan, Maanshan, Nanchong, Neijiang, Panjin, Pingdingshan, Puyang, Quzhou, Rizhao, Wuzhou, Shaoguan, Sanming, Shanwei, Shaoyang, Shiyan, Tongling, Xiangtan, Xining, Xuancheng, Xianning, Yulin, Yibin, Yingkou, Yongzhou, Yangjiang, Zhaozhuang, Zhangjiakou, Zhoushan
Fifth-tier cities	Ankang, Benxi, Baicheng, Baiyin, Baishan, Bazhong, Bayanzhuoer, Chaoyang, Chizhou, Chongzuo, Dingxi, Fuxin, Fangchengan, Fushun, Guangyuan, Guyuan, Guigang, Guangan, Hulunbeier, Hezhou, Hebi, Huludao, Jinchang, Jiayuguan, Jiuquan, Jinmen, Liaoyuan, Laibin, Liaoyang, Mudanjiang, Pingliang, Pangzhihua, Pingxiang, Sanmenxia, Songyuan, Shuozhou, Suining, Siping, Suizhou, Shizuishan, Shangluo, Tonghua, Tongchuan, Tianshui, Tieling, Tongliao, Qinzhou, Qiqihaer, Wulanchabu, Wuwei, Wuhai, Xinyu, Yingtan, Yaan, Yanan, Yunfu,-Yangquan, Zhangjiajie, Ziyang, Zhangye